Incorporating Traffic Management Information into Logistics Planning

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"Life is like riding a bicycle. To keep your balance, you must keep moving."

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Albert Einstein

Contents

List of Tables

List of Figures

List of Algorithms

List of Acronyms

ADP Approximate Dynamic Programming

B2C Business to Customer

B2B Business to Business

CLSP City Logistics Service Provider

DVRPMC Dynamic Vehicle Routing Problem with Stochastic Changes of Travel Time Matrices

GHG Greenhouse Gas

MDP Markov Decision Process

PTDS Partial Time-dependent Sampling

SDVRP Stochastic Dynamic Vehicle Routing Problem

TM Traffic Management

TMS Traffic Management System

TSP Traveling Salesman Problem

TT Travel Time

VRP Vehicle Routing Problem

Chapter 1

Introduction

Freight transportation fulfills the important task of moving a customer demanded product to a market where it can not be sourced. This allows the human population to have access to a wide variety of goods. The demand for transportation of products (i.e. food and leisure articles) is served by logistics service providers, who supply supermarkets, retail shops and deliver parcels directly to the customers of the continuously growing E-commerce market. To transport the large amount of goods from production to consumer sites, the logistics service providers use a fleet of delivery vehicles on the traffic infrastructure. In their operational planning, they decide which delivery vehicle transports which goods and in which sequence the customers are served in the delivery tours.

The customers of logistics service providers expect fast deliveries. Nowadays, they are also becoming more aware of the negative environmental impact of their deliveries and request a minimization of the carbon footprint of the transport activities from their logistics service provider. In contrast, customers are often not willing to pay more for a more environmentally friendly service (Gevaers et al. 2011). Freight transportation is, however, one of the main sources of air and noise pollution. Instead of focusing on their emission production, logistics service providers must focus on being profitable in their operational planning to survive in a highly competitive market. Logistics service providers have tried to improve their public image through air pollution compensation projects like carbon offsets or carbon credits. These projects realize a reduction of carbon dioxide or greenhouse gases in climate protection projects and are sold by for-profit companies, governments, non-governmental organizations and universities (Car 2008). The major city logistics service providers (i.e. DHL, UPS, DPD and Hermes) in Germany all participate in such programs. The programs are quite similar and suggest Greenhouse Gas (GHG) neutral shipping (DPD 2017, Hermes 2017, Ltd 2012, Service 2016). But except for a small number of additional E-mobility delivery projects, logistics companies do not try to reduce the air pollution production of their transport activities. In practice, logistics service providers services often ignore emissions in their fleet planning and focus on reducing costs and on improving efficiency and service level.

The resulting air pollution is, however, a major problem as it is a health danger for humans and in many cities worldwide, an unhealthy level has been reached. Many state and city administrators try to reduce the transportation related pollution by improving the traffic infrastructure. The European Union passed the EU regulation 2008/50/EC, which limits the air pollution to 40 $\mu g/m^3$ of NO_2 in the yearly average in EU city areas. This pollution level is deemed by the EU as the barely healthy limit for its citizens. Many European city administrators have tried dynamic short term strategies to reduce emissions as they face expensive fines if they do not comply with the legal requirements. The cities of Rome and Milan in Italy for example banned cars from the road after emissions exceeded the regulated levels for 30 consecutive days. The city of Paris in France on the other hand has reduced traffic to half on days with extremely high pollution levels by temporary prohibiting the usage of either vehicles with even or odd number plates.

An emerging traffic infrastructure technology to reduce air pollution levels are emission-sensitive dynamic traffic management systems, which manipulate traffic flows by adapting traffic lights programs when the air pollution is high. In the two German cities Potsdam and Braunschweig, the dynamic environmental-sensitive traffic management systems are actually in operation. Both cities have local areas with very high air pollution well above the EU limit. These areas are called hot-spot areas. If the air pollution is high, the access for vehicles into those areas is restricted through gating. Gating is realized with traffic lights and limits a direction of travel through very long red intervals. Inside the hot-spots areas traffic is accelerated by coordinated traffic light intervals of adjacent intersections to reduce emission unfriendly stop and go behavior. The air pollution level can change quickly and can vary significantly throughout the city. The level does not only depend on traffic, but also on weather conditions. In these dynamic traffic management systems, the air pollution is measured constantly at all hot-spots and if the pollution exceeds a defined threshold level at a hot-spot the pollution-reducing traffic signal plan for this hot-spot is activated. Each hot-spot has an individual predefined plan to reduce further air pollution caused by traffic. The combination of all used plans and therefore the systematic adaption of the traffic infrastructure to a certain traffic-related situation is called a *traffic strategy*. The traffic strategies have a high influence on the traffic situation and therefore also on the delivery fleets of city logistics service providers. Currently, these traffic strategies are not communicated to traffic participants. Especially city logistics service providers should have benefits by knowing the traffic strategy and incorporating this information either in the initial distribution of the freight between the vehicles of the delivery fleet or for dynamic adjustment of the delivery routes to the traffic strategy. If a delivery vehicles travels into a polluted area, it could result in an substantial increase in costs (e.g. fuel, working hours) for the city logistics service providers through increased travel times.

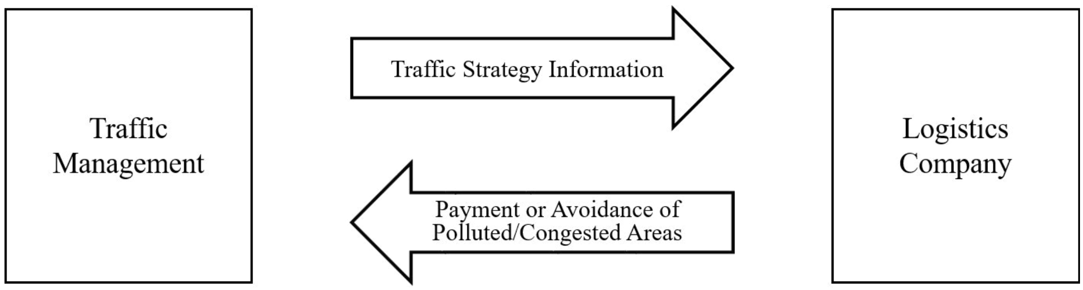


Figure 1.1: Cooperation between Traffic Management and a Logistic Company

In this thesis, the impact of a dynamic traffic management system on the delivery operations of logistics service providers is evaluated and the managerial implications of a possible cooperation are investigated. The features of a cooperation between traffic management and city logistics service provider are visualized in Figure 1.1. The motivation for the city logistics service company to use traffic management information is a potential decrease of fleet cost as costs are the main driver for their operational planning. As a byproduct the fleet could avoid congested and polluted areas or the logistical service provider could pay for the information, which all would be a strong motivation for the traffic management to share information about their traffic strategies. In the analysis, the focus is on an environmental-sensitive traffic management system and a city logistics service provider. The work is also transferable to traffic-sensitive traffic management systems and other types of logistics companies. In this work, managing strategies for integrating traffic management information into the operational planning for a logistics service provider are presented and the impact of the traffic management information for logistics is analyzed. In their planning, the objective of the city logistics service provider is to minimize the travel time of the delivery vehicles as driver wages are the main cost point in logistics. For the traffic management, the objective is to reduce the number of vehicles and time spent in polluted hot-spot areas. This is not optimized in this thesis as the focus is on the managerial actions of the city logistics service provider, but it could be a byproduct of logistics optimization. For the managerial implications for the city logistics service provider, the focus is on the operational city logistics service provider fleet routing where the traffic management system provides information about the current and near-future traffic strategy through the cooperation. The considered problem can be formulated as a special case of the vehicle routing problem: the *dynamic vehicle routing problem with stochastic changes of travel time matrices* (DVRPMC). In this special case, the assumption is that the travel time matrices depend solely on the traffic management systems traffic strategies and that the matrices transition stochastically. This problem has not been studied in literature yet, except for my previous work in Köster et al. (2017a) and another publication which is currently under review (Köster et al. 2017b). This thesis relates to both papers.

For the investigation of the research question, a case study of the environmental-sensitive traffic management system in Braunschweig, Germany is conducted. For the validity of the model, data about the hot-spots, the traffic strategies and a pollution dataset for each hot-spot is used. Due to the nature of the impact of dynamic environmental-sensitive traffic management systems on urban travel times, a number of deterministic travel time matrices exist in the problem. The transitions between different travel time matrices is, however, stochastic. Two variations (VRPI and VRPII) of the DVRPMC are used to research under which circumstances an effect for city logistics service providers can be measured. The VRPI investigates the simulation for a delivery company that has to face the stochastic travel time matrices induced by dynamic traffic management and a known set of customers. For VRPII additional stochastic customer requests are integrated in the problem. For the routing, different information settings regarding the traffic strategies are used to determine if knowing the traffic strategies of the dynamic traffic management can improve the delivery tours of a city logistic company. The focus of this work is to investigate the effect of the dynamic traffic management system on city freight companies. Therefore, state of the art routing software for delivery planning is used. The integration of anticipatory methods can additionally improve the routing solution, by incorporating potential future traffic strategy changes into the current decision making. To allow this, the method $partial\ time - dependent\ sampling$ is introduced, which constructs anticipating travel times matrices through simulating possible emission trajectories from historical data for the individual hot-spots. For the evaluation, two different decision types for logistics fleet planning are considered. First, the effect of initial distribution of parcels between the different delivery vehicles is investigated and then the effect dynamic routing decision making is analyzed. For the experiments, the effect of the traffic management on the travel speeds is varied in different speed scenarios and the effect of the variation fleet size of the city logistics service provider on the solution is investigated.

The parts of this thesis cover the following topics that are used to investigate the described problem:

Part I: City logistics and Traffic Management. Logistics activities in urban areas are fulfilled by city logistics service providers. As the focus of this work is on the impact of a cooperation between municipal traffic management regulations and logistic service providers, Chapter 2 highlights the city logistics industry and their challenges. Therefore, the chapter first covers the stakeholders of city logistics. The chapter then concludes with a view into delivery networks and methods for planning city logistics activities. In Chapter 3, the modeling of city vehicle routing problems is presented and in Chapter 4 the related Literature is shown. Traffic management systems are managing the traffic infrastructure and are an important part of today's traffic. Their goals, actions and the variants of dynamic traffic management systems are presented in Chapter 5.

Part II: Case Study. In Part II, the experiments for the case study are presented. Therefore Chapter 6, shows the possibilities of a cooperation between logistics and traffic management and relates this to the case study with an introductional example. The case study is detailed in Chapter 7. The model for the experiments is shown in Chapter 8. In the following chapters, the problem for the different VRPs is defined and the solution methods and the routing software Spider are presented in Chapter 9.

Part III: Computational Experiments. In this Part, the setup (Chapter 9) and results (Chapter 10) from the computational experiments are shown. The experiments show the expected benefits from a cooperation between city logistics service provider and traffic management. Furthermore, an in-depth analysis on how the behavior of the city logistics service provider changes with additional information from the cooperation is presented.

Part IV: Conclusion and Outlook. In the final part of this thesis, a short summary is given, the main outcomes are highlighted and an outlook is presented.

Part I

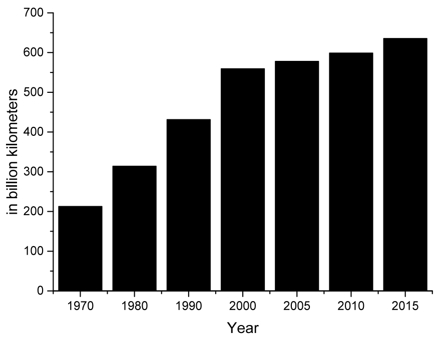
City Logistics and Traffic Management

Chapter 2

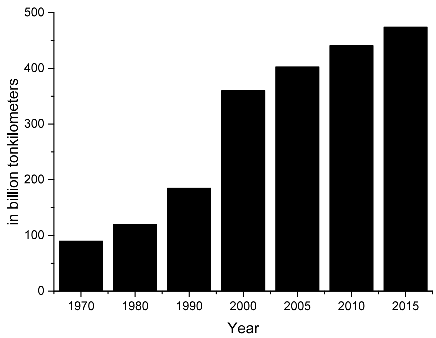
Transportation and Logistics

Transportation is one of the main components in human life and essential for many economic and social activities. The term describes a physical and therefore geographical movement (Nuhn and Hesse 2006). The freight transportation represents the movement of goods, often for commercial profit, by road, rail, boat or air transports and enables the availability of many goods and products for factories and customers. All realized freight transports, empty truck runs, and individual person transports constitute the traffic. The traffic itself and the amount and distance of transported goods are increasing. The annual car-driven kilometers for example, as shown in Figure 2.1a, have increased by nearly 200 % between 1970 and 2015. Reasons for that are an increased amount of young single-person households, who are very mobile, and the increased mobility behavior of seniors (Bundesministerium für Verkehr und digitale Infrastruktur 2008). The development of freight transportation indicates an even stronger growth than individual transportation by car as seen in Figure 2.1b, which shows the freight movement development in ton-kilometers in Germany. Ton-kilometers represent the movement of one ton of freight goods a distance of one kilometer and is therefore an important logistics performance indicator. The graph shows that freight transportation has grown by slightly more than 400 % between 1970 and 2015. The reason for growth are the globalization, the liberation of markets and freetrade agreements between countries. Another reason for the growth is the specialization of companies or their different company locations. The labor division of product productions also induces logically more freight transports than the complete production at a single production site.

The transportation of freight is part of logistics, which involves all activities re-



(a) Annual Driven Car Kilometers in Germany from 1970 to 2015 (Bundesamt 2015a)



(b) Road Freigt Transportion in Germany from 1970 to 2015 (Bundesamt 2015b, 2011)

Figure 2.1: Person and Freight Road Traffic Development

lated to the actual goods movement. It can be defined by the statement "*Logistics is the process of planning, implementing, and controlling the efficient, effective flow and storage of goods, services, and related information from point of origin to point of consumption for the purpose of conforming to customer requirements*" (Council of Logistics Management U.S., 1999). The logistics sector in the European Union amassed 2200 billion ton-kilometers (Commission 2016b) and had a market value of 878 billion Euro in 2012 (Commission 2016a). It is an important industry sector worldwide. Business forecasts show that the market for logistics operations is expected to continue to grow (American Trucking Association 2011) and therefore provides many opportunities for logistic service providers.

2.1 City Logistics

In 2010, about 50% of the human population of 7 billion lived in urban areas. This proportion will grow to 60% by 2030 (Taniguchi and Thompson 2014). The permanent movement of population from rural to urban areas is referred to as urbanization. In developed countries, 86% of the population will live in urban areas by 2050 (Economist 2012). This development, the increasing total human population and the ongoing growth of online shopping have led to a significant increase in freight traffic in cities. Forecasts show that this trend will continue (McCarthy and Knox 2005, Crainic et al. 2009a). The development of E-commerce, the process of buying products over the internet and shipping them as parcels to the customer, has steadily increased since its beginning. Figure 2.2 shows the growth and forecast of global Business to Customer (B2C) e-commerce sales in the timespan between 2012 and 2018. In the chart, in can be discovered that the E-commerce sales are expected to grow by 150% in the shows timespan.

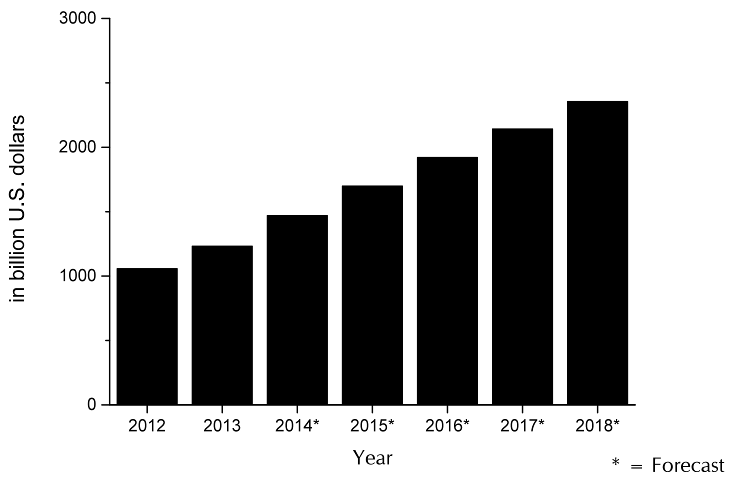


Figure 2.2: Global B2C E-commerce Sales from 2012 to 2018 (eMarketer 2016)

Nowadays, already about one fourth of the city traffic is related to freight transports (Dablanc 2007). City logistics service provider (CLSP) realize the transportation in this area. The fast growing parcel market has increased above average compared to other transport sectors because of the strong growth of e-commerce sales and is now a market with high cost pressure (eMarketer 2016). First, the high competition within the market forces CLSP companies to reduce shipping costs to be able to compete on the market. Secondly, large online retailer like for example Amazon have a strong leverage through their shipping volume on price for the delivery to their customers. And lastly, customers of the retailer expect fast shipping at low costs.

Logistic operations in cities are different from long haul logistics as many more aspects must be considered. Travel speeds are for example slower and more volatile due to limited road capacities, which are influenced by traffic, traffic lights, congestion and rush hours. The impact of rush hours on the travel time of street segments is especially high (Ehmke et al. 2012). When traveling between two points in a city, there are also usually a high number of suitable route options, when compared to a long haul trucking operation, which is bound to the highways. For a city logistics vehicles, it might be faster for a delivery truck to travel through the city center between two customers at one point in time and at a later point in time, a route around the city center might allow the vehicle to reach its destination faster.

Many cities have special policies and regulations for freight traffic. The goal is either to remove freight trucks from the city center or to lessen the environmental impact of the trucks through additional regulations for trucks. Logistics in urban areas therefore needs its own solution concepts. Mobile communication, location tracking of trucks and faster computer technologies now enable the integration many of these challenges into the planing process. CLSPs can now redirect their vehicles when new information is available to the dispatcher or even anticipate future conditions like customer pick-up requests or traffic situations. From a decision making aspect this is called *Dynamic Decision Making*. Good concepts for city logistics will get more important in the future due to the shown trends of increased city freight transports. These special delivery concepts for urban areas and the associated research is defined as *City Logistics*. A good definition of city logistics is given by Taniguchi et al., who describe city logistics as

the process of totally optimizing the logistics and transport activities by private companies in urban areas while considering the traffic environment, the traffic congestion and energy consumption within the framework of a market economy (Taniguchi et al. 2001).

For CLSP, the growing market provides a chance for an increased revenue for companies, who can increase their market share. CLSP companies also face growth related challenges. An increased shipping infrastructure is needed to handle the demand. The planning of the logistical processes of the increased number of shipments must be done with state of the art planning approaches to be cost efficient and to ensure long term business success.

2.2 Stakeholders

An urban area is densly populated, so a conflict arises from different interest and needs. The number of involved stakeholder for city logistics is higher than in classical logistic operations (Taniguchi and Thompson 2002). The stakeholders of urban logistics delivery are classified into residents, shippers, freight carriers and administrators Taniguchi and Thompson (2014). These stakeholders all stand in a relationship to each other and have different, sometimes opposing, interests and goals. Figure 2.3 shows the interaction of the stakeholders among each other. Each decision made by a stakeholder also influences other stakeholders as they share the same urban environment (Kim et al. 2015). This is symbolized with two-sided arrows in the figure. In this research, the main focus is on the interaction between logistics service providers and traffic management, which is a tool of the city administrators. The two-sided interaction arrow for this relationship is therefore enlarged compared to the other stakeholder relationship arrows in Figure 2.3, which are discussed as well.

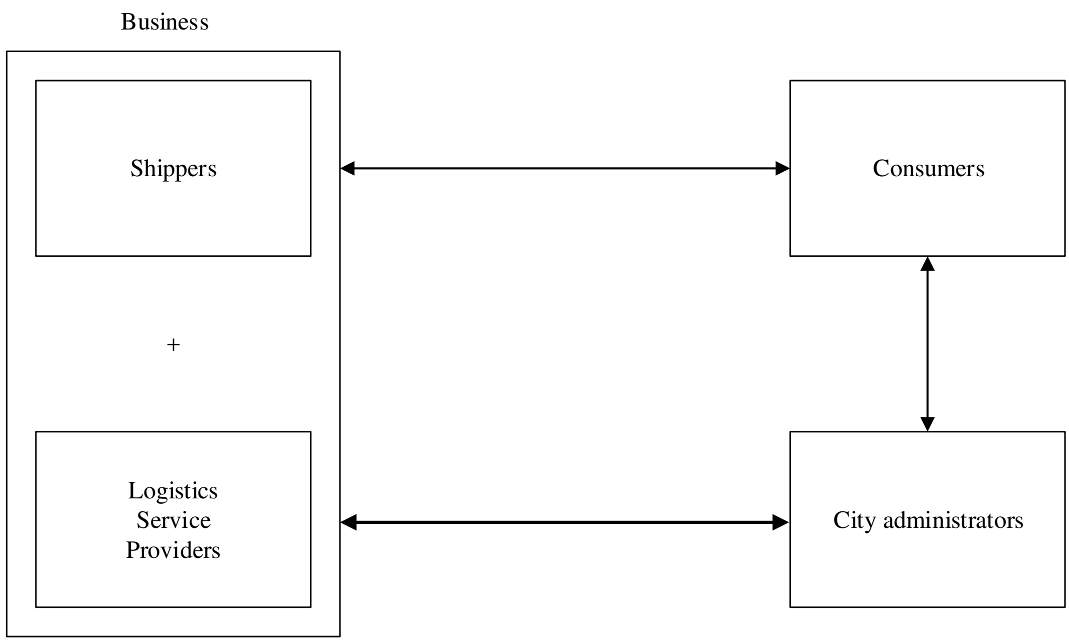


Figure 2.3: Interactions between Stakeholders adapted from (Nemoto et al. 2001)

The interest of the residents is a reduction of traffic congestion, air and noise pollution and the realization of many work and leisure opportunities. Urban freight transportation offers many jobs for city residents, but freight vehicles in cities also contribute to congestion and pollution. Freight companies therefore negatively impact life quality of the residents (Crainic et al. 2009a, Figliozzi et al. 2007). The shippers represent the manufacturers and/or retailers of goods. They send their goods to other business companies or to the residents, which are their customers.

The objective of the freight companies is a fast delivery with a high service level and a high reliability. Taniguchi et al. states that the shippers' interest is an undelayed delivery process that does not damage the goods and arrives at the designated arrival time at the customers location (Taniguchi et al. 2001). CLSP are defined as the freight carriers and handle the actual deliveries in city logistics, which could be B2C or business-to-business (B2B). They pick up the cargo at a distribution center or directly at the shipper. The CSLP uses a fleet of vehicles for the deliveries, which are routed to the customers. From the residents perspective, it often seems that shipper and carriers are a single company. The city administrators (also defined as government or city municipality) work on the city's social and economic development to improve the life quality for residents. Summarized, their goal is to improve the city environment for the other stakeholders (Taniguchi and Thompson 2002). One of their tools are traffic management systems, which manage the traffic infrastructure and thereby influences traffic flows to improve all traffic and transportation related activities. Traffic congestion is a major problem not only for the traffic management, but for all stakeholders nowadays and leads to air and noise pollution as well as unnecessary time spent with transportation activates. According to the European Commission, 9 out of 10 European residents believe that their cities traffic situation could be improved. Consequently, many cities try to reduce their traffic situation with a better traffic management.

2.3 City Logistics Networks and Initiatives

Classical hub-and-spoke networks of courier, express or parcel service providers (CEP) handle the immense load of parcel freight from the e-commerce. The deliveries are usually split into different transport legs to reduce transporting costs by achieving higher vehicle load rates. In hub-and-spoke networks of the parcel industry as seen in Figure 2.4, a vehicle picks up goods ordered by customers and packed as parcels at an online retailer and transports them to the closest hub, which in this case is defined as hub A. Warehouses of large shipping retailers can already act as the outgoing distribution hub. From there, it is transported with a larger long-haul transport to the hub (B) that serves the area to which a parcel is delivered to. The long-haul hub to hub transports are often realized overnight. Inside a hub, parcels are sorted by a network of fixed cross conveyors. Therefore, each hub has specified loading ramps for incoming and outgoing long-haul transportation to and from other hubs. From here in the last part of transport chain, the parcels are delivered with smaller delivery vehicles to end customer (Bontekoning 2006). This concept has many advantages as it reduces cost through higher load rates of the vehicles. The last part is defined as the *last-mile delivery* and is responsible for more than 50% of the overall delivery costs (Bernau et al. 2016). This shows the complexity and truck/labor intensive side of last-mile-delivery. In this research, the focus is on the last-mile delivery, because it has the highest interaction with the traffic management. For the last-mile delivery transport, CEP use a fleet of vehicles to make individual deliveries stops at each customers. Therefore, first the parcels must be split up between the all delivery area serving vehicles. Then, the dispatchers of the CEP have to route each vehicle to its customers for whom they carry the load. A good ordered customer delivery sequence can significantly reduce costs. Nevertheless, the number of stops and the volatile environment of urban traffic often makes the planned routes inefficient. The quality of split and routes, of the delivery fleet for the last-mile delivery has a significant impact on profitability of the CEP and is the focus for the logistics activities in this work.

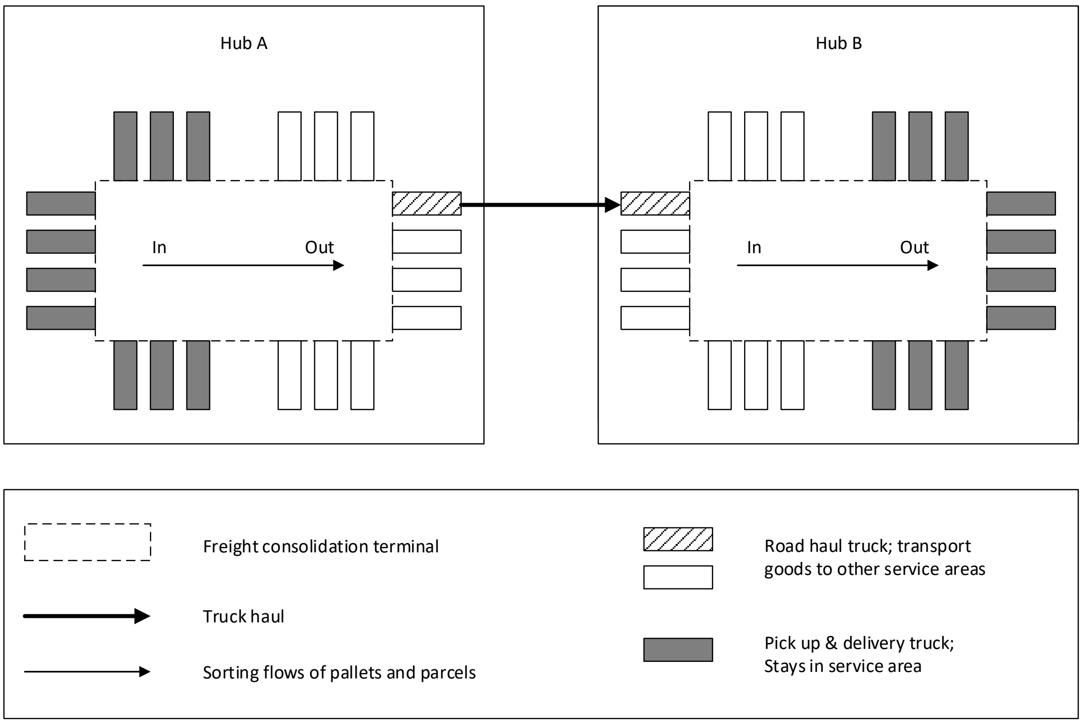


Figure 2.4: Schematic Representation of the Organization of a Hub-and-Spoke Network for the Parcel Industry adapted from Bontekoning (2006)

One idea for a more efficient city logistics process to which are research can be applied as well are *City Distribution Centers* (CDC). City Distribution Centers are structured similarly like hub-and-spoke networks, however, a major difference is that more than one company can use the CDC. The major idea is not to recognize the shipments of companies individually, but to see the city as an integrated logistic system (Crainic et al. 2009b). This is achieved through consolidating Business-to-Business (B2B) freight transports of different freight carriers for the last-mile. So instead of an individual delivery to a local shop by a large truck, the deliveries are sent to the CDC where they are consolidated with other freight for the last-mile-delivery in a smaller vehicle. This reduces the number of large trucks in the inner-cities significantly and has a positive effect on traffic and air pollution. CDCs are operated by private companies, who often receive government funding, or directly as a government initiative. In the early seventies, the number of CDCs for consolidated inner-city shop deliveries increased significantly in many European cities, especially in Germany. Many projects however folded after the initial funding expired and of 200 planned or realized projects only 15 still exist in 2002 (Crainic et al. 2009b). The problem for the shops were often additional costs, an increased organizational effort and the fact that a reduced traffic load in the city is not of interest for shops. The operators of the CDCs also faced obstacles in providing an efficient urban logistic system. Often not enough city shops were interested in the service. This results in less efficient cargo consolidations. CDCs must improve their cost models, discover how to create additional value to their service for shopkeepers and secure municipal funding or special allowances for inner city-deliveries to be relevant in the future (Taniguchi and Thompson 2014).

2.4 Last mile delivery

Last mile delivery is very complex due to city congestion and a high number of customers per vehicle. As stated before, it is responsible for more than 50% of the overall delivery costs (Bernau et al. 2016). One of the main issues in the last mile delivery is the percentage of failed first time deliveries to the customer. A failed delivery occurs when a parcel can not be placed adequately according to delivery method for the customer. This results in a second delivery try on the next day, which essentially doubles the CLSP's cost for this parcel. A second delivery try does not seem like a lot of effort, however as the number of failed deliveries is high, this is significant. Many different delivery options exist today and they are shown in Figure 2.5. Today, the most common delivery option, especially for e-commerce shipments, are home deliveries (Allen et al. 2007). Each customer receives the individual delivery to a self-defined address. This is often the customers' home address, but often deliveries are also sent to the customers' workplaces. The delivery to self defined location is either of an attended or unattended type. For the attended delivery, the CEP needs a delivery conformation signature and is often associated with goods of higher value. This requires the customer to be physically present in order to accept the shipment. The majority of failed deliveries occur in this case and happen if the specified delivery location is unattended by the customer. This is especially true if no delivery time window was specified by the customer (Gevaers et al. 2011). The unattended delivery does not require the customer to be presented and the shipments are either delivered to a present neighbor or to a customer delivery box. If a delivery fails or if the customer chooses, it is also possible for him to pick up the shipment at various pick-up locations. This can be at the CDC, a city shop, a reception box with pin code, at collection points or at a post office. In this research, we focus on attended home delivery.

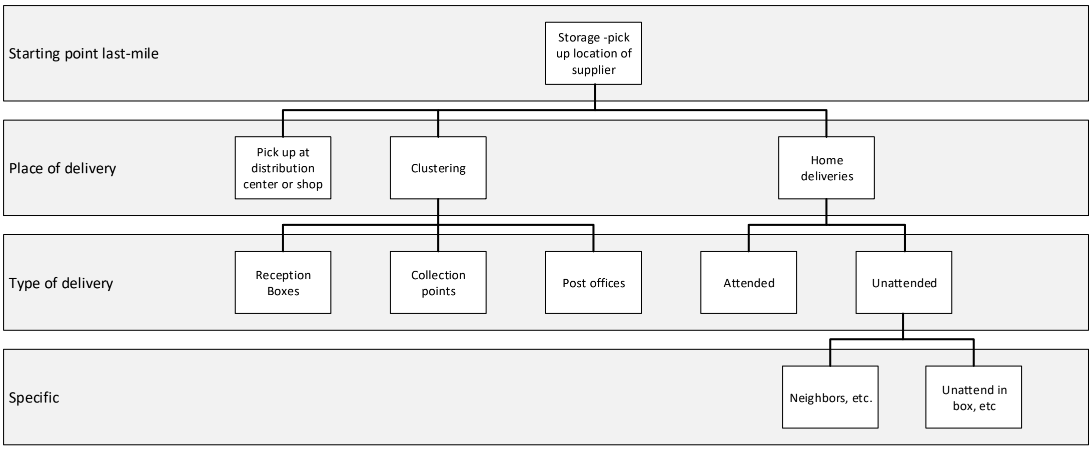


Figure 2.5: Delivery Methods in Last Mile Delivery (Gevaers et al. 2011)

Chapter 3

Modeling of City Vehicle Routing Problems

In Section 2, the environment for city logistics operators was detailed. In this section, the focus shifts to how such transport tasks can be modeled, solved and optimized with operations research techniques. Furthermore, the specialties of the modeling a city logistics environment are shown and which reasons for uncertainties exist for the logistics service provider. The main motivation for using operations research techniques for CSLP is either when locations for a new depot searched or when daily operational deliveries have to be organized or improved. Logistics problems are often modeled as a vehicle routing problem (VRP). The VRP was first described by Dantzig and Ramser in 1959 to solve a petrol delivery problem (Dantzig and Ramser 1959).

The traveling salesman problem (TSP) represents a special case of the VRP. The problem focuses on a salesman, who has to visit a series of customers with his car. Therefore he starts at his home location and after visiting each customer location, he has to travel back to his home location. The task is to find a tour that does not only fulfill the constraints of visiting each customer and then returns the salesman back to his home location, but to find the tour with the shortest distance or smallest cost ,depending on CLSP objective. An exemplary TSP is given in Figure 3.1, where five customers and a depot, which represents the start and end location of vehicle, exist. The problem consists out of a Graph $\mathcal{G} = (\mathcal{N},\mathcal{E},\mathcal{M})$. The customer are represented as nodes $\mathcal{N}$, the paths between the different locations as edges $\mathcal{E}$ and a distance matrix $\mathcal{M}$ that describes the distances between the different locations. Mathematically, the

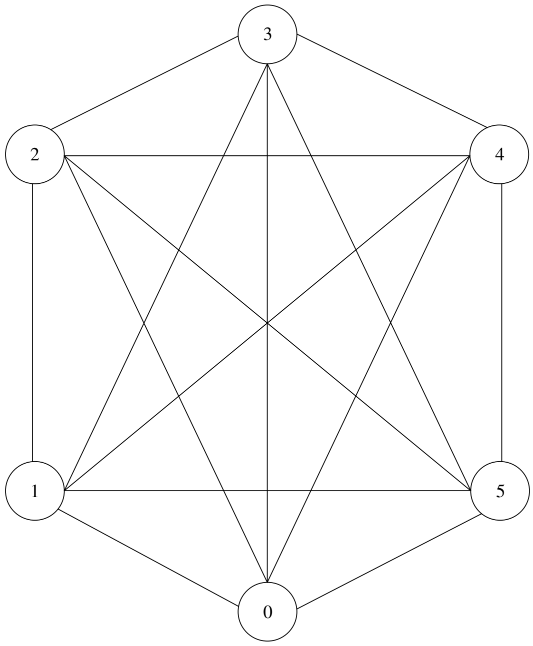


Figure 3.1: An Exemplary Traveling Salesman Problem

problem can be formulated as an Integer Programing Problem:

$$\text{minimize} \sum d_{ij}x_{ij} \tag{3.1}$$

$$\sum_i x^{ij} = 1, j = 1, ..., n \tag{3.2}$$

$$\sum_j xj = 1, i = 1, ..., n \tag{3.3}$$

$$\text{The variables } x_{ij} \text{ are not allowed to form a subtour} \tag{3.4}$$

$$x_{ij} \in \{0{,}1\} \tag{3.5}$$

The decision variables x_{ij} denote if a path between a node i and node j is used. In this formulation, x_{ij} equals 1 when the edge is used in the solution of this VRP and x_{ij} is 0 when the edge between nodes i and j is not used in the solution. A solution represents the outcome of the solved problem, which in this case is a tour for the TSP. The objective (3.1) is to find the solution that minimizes the traveled distance of the traveling salesman. The distance d_{ij} of each edge is of course fixed, but which edges are used in the solution is the searched decision (where $x_{ij} = 1$). The equations (3.2 - 3.5) describe the constraints. In a solution, each node is only allowed to have an entering and one leaving edge through the limiting equations (3.2) and (3.3). This guarantees that each customer is visited only once. Subtours can cause problems in TSP optimization as they lead to theoretically feasible solutions where all constraints are satisfied. A solution with subtours has multiple in itself closed tours, which are not connected to each other. Such a solution can, however, not be served in the real world as a only subtour is connect to the home location of the traveling salesman. Many different approaches to solve the subtour problem exist today as for example the Miller-Tucker-Zemlin constraints. In this theses, this is summarized in (3.4) as it is not a focus of this thesis. In an Integer Programming formulation, the decision variables x_{ij} can only take an integer value, because the salesman either uses a path between two nodes or not. This is enforced through constraint (3.5).

A solution to this problem can be achieved by an exact or heuristic solution method. An exact solution method reaches the optimal solution. A heuristic solution method can, but does not necessarily, obtain the optimal solution. However, in contrast to the exact solution, heuristics can find a solution faster due to shorter run times of the corresponding algorithms. The exact solutions require a significantly higher amount of computer calculation time. This is especially true for problems with a high number of customers as the complexity grows exponentially $(number\ of\ customers - 1)!$.

3.1 Modeling and Evaluating City Logistics Problems

Since the first described VRPs and TSPs, the problem has evolved and is applicable for many transport planning problems like city logistics problems. Models are used to virtually reproduce a problem and are in essence a simplified representation of the urban freight system. The main goal is to evaluate the performance of future city logistics concepts or operational changes to an existing one. Therefore, a model needs an algorithm or a policy to solve it. Standard problems that occur in city logistic operations are for example delayed deliveries through congestion, high costs and environmental impacts that need to be reduced. The urban environment is complex due to the number of involved stakeholder, the number of customers, the traffic network geometry and traffic management systems. Consequently, current models are still limited in predicting every outcome accurately as many variables and constraints must be considered. According to Taniguchi and Thompson (2011), current mathematical models are not sufficient to fully describe an urban transport system and that validating and calibrating a model is a challenge (Taniguchi and Thompson 2011). However, models and the evaluations of their solutions are useful for decision makers. They can be used for the complete planning or just as a decision support tools to get an indication for a real-world city logistics problem.

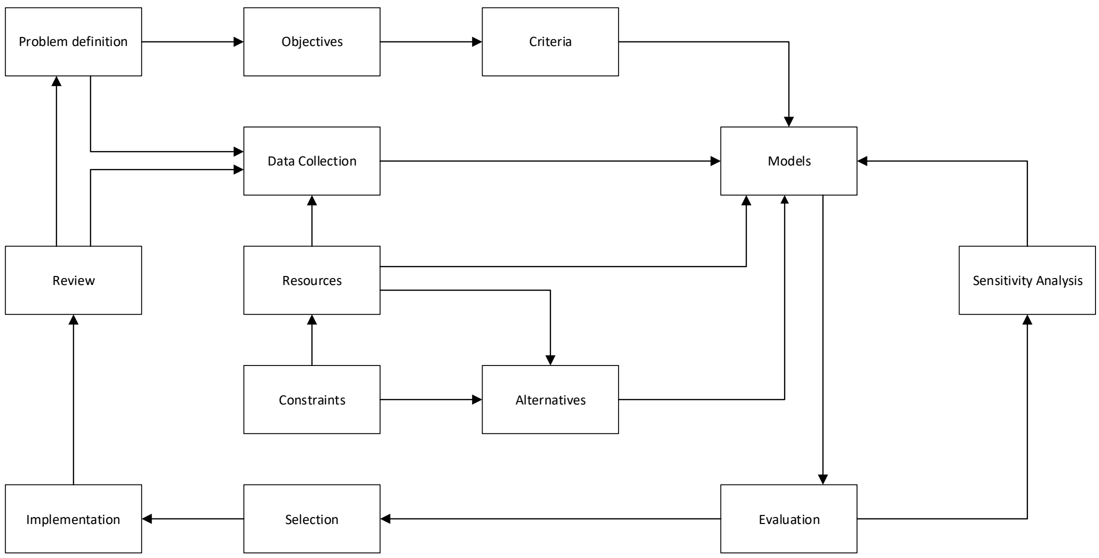


Figure 3.2: Modeling and Analysis of City Logistics Problems (from Taniguchi and Thompson (2011), adapted by Ehmke (2012))

Figure 3.2 shows a framework for modeling and evaluating city logistics delivery problems. Here, the problem is first defined, which symbolizes the difference at a point in time between an actual and a desired state of a system (Taniguchi and Thompson 2011). Therefore, the situation of all involved stakeholders and their interactions is analyzed. Then, the attributes of the problem influencing factors are quantified. Objectives in models are used as a goal. This could be a reduction of cost and environmental impact or to increase a system in efficiency. These goals are further specified in criteria, which are value based key performance indicators of the objectives. They allow quick and effective evaluation whether a new concept will be successful or not. Here, examples are load factor, number of required trucks, delivery time and the delivery success ratio for attended deliveries. Important for the model are also the available resources for the city logistics project. They are inputs to the model and include not only the planning resources like budget and human skills, but also public resources like the transportation infrastructure. They are restricted by the constraints, which can be the availability of required resources, budget restrictions or governmental regulations for example. The alternatives are the options for a CLSP that have the potential to solve the problem and have to be evaluated. The options range from a strategical decision when evaluating locations for CDC, to a tactical decision when planning the weekly workforce or operational variations in the computerized vehicle routing. The data collection is used to quantify every aspect of the model more accurately to improve its correctness. Data can preexist or has to be collected specifically for the model. The data can be static, for example the transport network geometry, or dynamic like the real time travel times. It can also be deterministic, which means the data is correct, or probabilistic and can come from public or private sources. Data can be various information, but for city logistics the following information is useful:

- Transport network geometry

  This defines the transport infrastructure that is used in the model for the service area. Simple models tend to use the Euclidean plane, where the problem is modeled in a road less plane. Customer locations are assigned to a x/y coordinate and the distance between customers is the airline distance. With the emergence of digital maps, it is possible to create an accurate virtual representation of a real-world transport network geometry. Digital maps are often managed in *Geoinformations Systems* (GIS) and are widely available. Internet platforms like OpenStreetMap offer maps for free and are based on crowd-sourced measurements. A digital map consists of individual lines and points. Each street segment has a variety of attributes depending on the data source. This can be for example street length, street names or specific street restrictions like one-way streets. Traffic management measures that have an influence on traffic can also be part of the Transport network geometry. Travel times for street segments can be derived by assuming a certain travel speed.

- Historical travel times

  Travel times can be derived from historical travel time data. This data is usually collected as Floating Car Data (FCD). This means vehicles are equipped with sensors for the physical position on earth via satellite navigation systems (GPS, GLONASS or Galileo) and record their position in predetermined time intervals. These single data points are combined to a track, which is an ordered list of individual data points. The track must be filtered and processed so it can be matched to the transport network geometries' street segments. A matched track is then cut into parts of individual street segments for individual travel speed observations for that street segment. Travel speeds of a recorded street segment can be calculated with the time and distance between the individual points of the track or sometimes the individual track points have a speed attribute that is recorded by the vehicle at the time of the data point. This is done for all tracks of all collecting vehicles. The associated track parts of unique street segments are then averaged for an expected travel time and a standard deviation can be calculated. The observations for individual street segments are usually split into time intervals for time-dependent travel times to increase the accuracy. Many public transportation companies or CLSP have equipped their fleet with the required technology. Over any given time, this leads to a huge amount of data from the collecting vehicles, but FCD data has become valuable and provides a good estimation for travel times in city logistics models.

- Real-time travel times

  Real-time travel time data is also FCD, however, it differs from historical travel times in the form that collected data points are instantly transmitted to a server for real-time travel time via mobile data-transfer technology. This allows real-time traffic information and can be directly used for a planning task. Therefore, the current traffic conditions can be recognized in the planning to avoid congestion or accidents. Weather can also be an influencing factor for travel times. Heavy rain and snow can significantly reduce driving speeds and therefore increase travel times.

- Vehicles

  The dispatcher of the CLSP guides the delivery vehicles through the transport network to deliver or pick up goods or perform a service at customer locations. Many times, the vehicles have a common start and end location, which is defined as the depot. The task of the dispatcher is to decide which customers are served by which vehicle and then to create a route for each vehicle, which sequences its customers and the depot into a tour. For this decision, the dispatcher needs the fastest path matrix between locations (time or distance). This can be derived distance-based from distances of the individual street lengths of the transport network geometry or time-based from the travel times of individual street segments as described earlier.

The vehicle fleet has specific vehicle attributes that must be considered in a model. The fleet itself can have a homogeneous or heterogeneous nature. Each vehicle has restrictions that can limit their usage. Each vehicle has for example a certain freight capacity, which limits the size or weight of the freight. The vehicle can also have a travel distance limit, which is enforced through the amount of on-board fuel or in case of an electrical vehicle by the battery capacities. A vehicle can have a working time capacity, which is set by the working regulation for the driver. Furthermore, vehicles specific attributes that limit or enable certain orders. Examples are loading cranes, cooling department or municipal usage prohibitions for certain areas by vehicle capacities, engine types or emission production.

- Customers

  The customers are the entities that require the service or deliver/pick-up of freight from the CLSP. Each customer has a specific location in the service area that can be mapped to the transport network geometry. Customers have a specific demand, which can be homogeneous or heterogeneous. The demand can be deterministic or stochastic. Each customer can have a defined service time or fulfillment time window, in which the customer should be served. Additionally, customers can require certain vehicle or driver specific capabilities. A successful delivery results in a reward, which usually is the requirement for delivery fee payment. A violation of defined service times or the time windows can result in a penalty or customer dissatisfaction, which represents the service quality. For a model, customers requests and demands are often stochastically derived from land use patterns, from historic customer request data or generated from a distribution.

The model is in essence a simplified representation of the urban transportation system. A model needs quantitative methods to find a solution and to be able to analyze all possible actions and alternatives based on economic, social and environmental performance factors (Taniguchi and Thompson 2011). The impact of specified parameters on the outcome can then be evaluated with a sensitivity analysis through variation of the parameters. After the final evaluation, a company decision maker can select an alternative and start the implementation which can be complicated with the number of involved stakeholder in city logistics. In the last step, the process is reviewed and changes to the problem definition and data collection might be made for future projects.

3.2 Dynamic Decision Problems

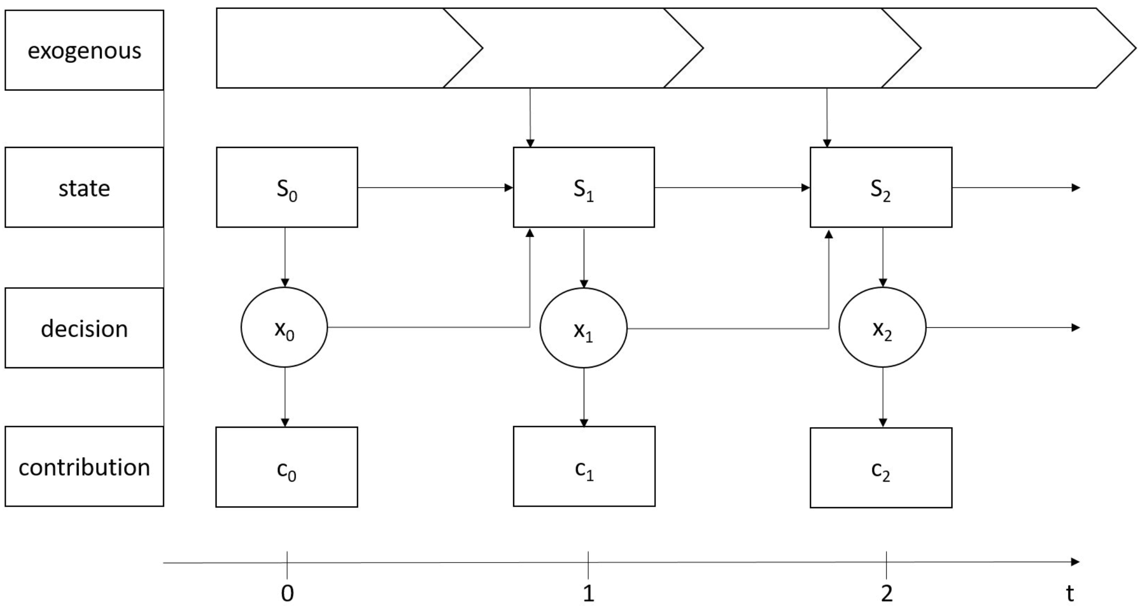


Figure 3.3: A Dynamic Decision Process (adapted from Meisel (2011))

Dynamic decision making describes the permanent re-adjustment of a plan to changing influencing factors to improve the outcome of the plan. When the framework for the model is defined, the setting for individual decisions must be described as well. Figure 3.3 shows a basic dynamic decision process, which in essence symbolizes a series of decisions for a model, also defined as a system, in a temporal order. A certain situation in a model at decision point k is represented by a state s_k, which describes the systems attribute's. The dynamic decision process starts with an initial state S_0 at the first decision point. In general, a decision point k occurs at time t_k and a decision x_k under consideration of state s_k has to be chosen from a set of possible decisions. To conduct a decision, the related contribution c_k is performed on the system. In order to find a good decision, optimization techniques can be used. After taking a decision x_k, the system state transitions to $s_{\mathrm{k+1}}$ for the next decision through the decision and the exogenous impact on the system that happens between decision points.

3.2.1 Dynamic Decisions with the Markov Decision Process

A specialty of the dynamic decision process formulation is the Markov Decision Process (MDP), which is especially suitable for stochastic and dynamic decision making problems (Bellman 1957). The MDP is independent of the solution approach. In vehicle routing, the problem is finite as the decisions in delivery routing end at a certain time, because of vehicle capabilities or working time restrictions of the driver. Decision are made at defined discrete decision points and are not continuous.

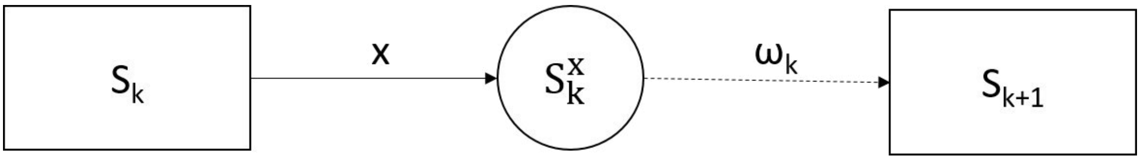


Figure 3.4: A Markov Decision Process (Ulmer 2017)

The MDP has several key features that distinguish it from other decision frameworks. The main feature is that the state s_k and the contribution c_k are independent of the their respective condition at the previous decision point $k-1$. The state s_k is therefore the sole criterion for the decision x_k. In a MDP, decision points $K = 0, ..., K-1$ occur in a temporal order. The length of K is determined by the time horizon of the problem. Actual decision points are triggered by events or by decision makers when they see a need for a different realization. Consequently, the time intervals of t are not necessary constant. S denotes the set of all possible system states and is defined as state space. A state itself usually is classified by a number of system parameters. X denotes the set of decisions. Notably, as a decision at decision point k is based on the current system state S_k, not all decision options may be available, because some decisions may have required prerequisites. The available decisions $X(S_k)$ are a subset of the complete decision space of $\mathcal{X}$. Figure 3.4 shows a single MDP decision process. In the state S_k, a decision x is conducted. This leads to the post decision state S_k^x. Afterwards, S_k^x is affected by the stochastic impact ω

and transitions to $S_{\mathrm{k+1}}$.

3.3 Modeling Vehicle Routing Problems

As noted before, city logistics problems can be modeled as Vehicle Routing Problems. All VRPs are modifications of the well-known Traveling Salesman Problem (TSP). Pillac et al. (2013) classifies the VRP into four types by two categories: type of evolution and quality of relevant planning information. Each category has two attributes as shown in Table 3.1. The information input in a model is either know beforehand or it changes over time. Accordingly, the decision process is either static, which induces that all planning activities with beforehand known information are done before the operational execution phase or the decision process is dynamic where re-planning for changed information is applied during the operational phase as specified in the last section. A second classificator is the information quality, which describes whether information is stochastic or deterministic. If all information is certain, it is defined as deterministic information. Stochastic information on the other hand is not certain and changes over time during the operational phase.

Table 3.1: Taxonomy of Vehicle Routing Problems by Information Input (adapted Pillac et al. (2013))

		Information Quality	
		Deterministic Input	Stochastic Input
Information Evolution	Input Known Beforehand	Static and Deterministic	Static and Stochastic
	Input Changes over Time	Dynamic and Deterministic	Dynamic and Stochastic

City logistics VRPs are often modeled as dynamic and stochastic as one or more information data inputs is stochastically. As the focus of this work is on a dynamic and stochastic formulation, an example of a dynamic and stochastic city logistics network formulation is presented in the following section.

3.3.1 State Space of a VRP

The state space is defined by all modeled system attributes and their range. A state S_k of the state space S is defined by the condition of each attributes. Table 8.2 shows a set of possible mathematical formulated attributes for a state space of a VRP model. Different VRPs usually have different models as well. Therefore, some models do not require all attributes and some may require different or additional attributes.

Table 3.2: Modeling a VRP State Space (adapted from Ulmer (2017))

Planning Element	Mathematical Formulation
Point of Time	$t \in \mathbb{R}_+$
Transport Geometry of Service Area	$\mathcal{G}$
Depots	$\mathcal{D} = \{D_1\} \subset \mathcal{G}$
Customers	$\mathcal{C} = \{C_1, ..., C_n\} \subset \mathcal{G}$
Vehicles	$\mathcal{V} = \{V_1, ..., V_i\}$
Travel Distance of l_1 to l_2	λ (l_1,l_2) $\in \mathbb{R}$
Travel Time of l_1 to l_2	$\tau(l_1,l_2) \in \mathbb{R}$
Demand of C_i	$c_i^{\text{demand}} \in \mathbb{R}$
Time Window of C_i	$(t_i^{\text{first}}, t_i^{\text{last}})$
Service Time of C_i	$t_i^{\text{service}} \in \mathbb{R}$
Demand of C_i	$c_i^{\text{demand}} \in \mathbb{R}$
Status of C_i	$\mathrm{r}(C_i) \in \mathbb{N}$
Travel Distance Matrix	$\mathcal{M}^\lambda$
Travel Time Matrix	$\mathcal{M}^\tau$
Position of V_i	$l_i \in \mathcal{G}$
Capacity of V_i	$v_i^{\text{load}} \in \mathbb{R}$
Fill Level of V_i	$v_i^{\text{fill}} \in \mathbb{R}$
Status of V_i	$\mathrm{r}(v_i) \in \mathbb{N}$
Working Hours of V_i	$(t_i^{\text{begin}}, t_i^{\text{end}}) \in \mathbb{R}^2$

For the modeling of planning situations, time is an important factor. It is modeled as $t \in \mathbb{R}_+$ and can only be numerically positive. Unlike in the real world, time is modeled in discrete time steps because a continuous time model is not realizable. The transport geometry of the service area $\mathcal{G}$ is represented by the connected graph $\mathcal{G} = (\mathcal{N},\mathcal{E},\mathcal{M})$ through nodes $\mathcal{N}$, edges $\mathcal{E}$ between nodes and distance and travel time time matrix $\mathcal{M}$. The vehicles $\mathcal{V} = \{V_1, ..., V_i\}$ can travel on the graph. The depot $\mathcal{D} = \{D_1\}$, where the vehicles start and end their tours, and customer locations $\mathcal{C} = \{C_1, ..., C_n\}$ are located on Nodes $\mathcal{N}$. The graph has nodes that are intersections between edges $\mathcal{E}$ and consequently not each node is a customer or the depot. Many edges are undirected, however, a subset of directed edges that represent one-way streets exists. The travel time τ and travel distance λ between two nodes n_1 and n_2 can be derived from transport geometry $\mathcal{G}$. The travel time and distance between every customer and depot can be specified in the travel time matrix $\mathcal{M}^\tau$ and $\mathcal{M}^\lambda$. The customers are the entity that require a service, a delivery or a pick up from the vehicles. Each customer has a certain individual demand c_i^{demand}, time window between t_i^{first} and t_i^{last} and a service time t_i^{service}. Each customer also has a status r(C_i), which indicates has if he been serviced yet. A status of $r(C_i) = 1$ means the customer has been served and $r(C_i) = 0$ indicates a service is still required. Each vehicle v_i has an individual location in the transport geometry. The capacity of each vehicle is v_i^{load} and amount of used capacity is represented by the fill level v_i^{fill}. Each vehicle i has a status as well, for example if it is currently en-route to a customer, unloading or waiting for a task. The vehicle has a specified maximum working time, which is limited by the drivers working time between t_i^{beginn} and t_i^{end}.

3.3.2 Decision policies and evaluation

Table 3.3: Elements of the Decision Policy (adapted from Ulmer (2017))

Planning Element	Mathematical Formulation
Routing	$\Re_i$
Route	Θ_i
Individual Route Stops	θ_i^z
Tour Duration	$\overline{\tau}(\Theta_i) \in \mathbb{R}$
Tour Length	$\overline{\lambda}(\Theta_i) \in \mathbb{R}$

Decisions in vehicle routing can be about accepting/rejecting customer service requests, the fill level v_i^{fill} of each vehicle at the beginning of a tour for cases of unknown customer demand or the routing to find a good tour, which includes the customers and start and end point at the depot in an optimal or near-optimal sequence. Decision making requires a policy that can choose between the decision options $X(S_k)$. A policy implies a solution method, which can find a solution to decision problems in the model. For VRP models, many different solution methods exist.

In this thesis, the focus is on routing decisions. The routing $\Re_i$ is the act of subsequent decisions $x_k \in \mathcal{X}$ for each vehicle about which customer to service next and requires a policy. A policy is the outcome of a process to choose a decision in a rational manner with the help of a solving algorithm. A route of a vehicle is the sequence of customer and depot visits $\Theta_i = (\theta_i^z, \theta_i^{z+1}, \theta_i^{z+2} ..., \theta_i^Z)$, where parameter z describes the number in the sequence for individual stops.

$$\overline{\tau}(\Theta_i) = \sum_{z=0}^{\text{Z-1}} (\tau(\theta_i^z, \theta_i^{\text{z+1}})) \tag{3.6}$$

A complete route is called a tour and its delivery travel time $\overline{\tau}(\Theta_i)$ is the sum of the individual trips z between the depot at beginning and the end of the tour and the customer stops without the duration of the service time at each customer as shown in Equation 3.6

$$\overline{\tau}_{\text{fleet}} = \sum_{i=0}^{I} (\overline{\tau}(\Theta_i)) \tag{3.7}$$

The duration of all tours from the complete fleet $\overline{\tau}_{\text{fleet}}$ of a CLSP company is defined as the total delivery travel time and is calculated by with the sum of each $\overline{\tau}(\Theta_i)$ as seen in Equation 3.7.

Chapter 4

Literature in City Logistics

In this section, an overview of the related literature is presented. We first focus on city logistics publications and then investigate vehicle routing problems with non-deterministic travel times. Therefore, we briefly look at VRPs with daytime-dependent travel times and then conduct an in-depth analysis of vehicle routing problems with stochastic travel times. In the end of this chapter, green vehicle problems are reviewed and it is shown how and why they differ from our problem.

4.1 Research in City Logistics Planning

The increase in urban population and freight transports has led to the need for more city logistic research (Kim et al. 2015, Cattaruzza et al. 2015). Consequently, research activities have increased steadily over the last decades. Figure 4.1 shows the cumulative and individual number of papers that were published about city logistics by decades between the years 1980 and 2016. It can be seen that after a small number of publications between 1980 and 1990, the research interest increased in the 2000s. In the current decade (2010-2019), the publications increase exponentially. Notably, by time of creation of the graph, this decade was not completed, so the paper output will be higher by the end of this decade. Even though the literature concerning city logistics increased significantly, (Crainic et al. 2009a) still states that,

"City logistics also challenges operations research to develop the appropriate design, evaluation, planning, and operation model, methods, and decsion-support systems. Contributions answering this challenge are still limited in number, how-

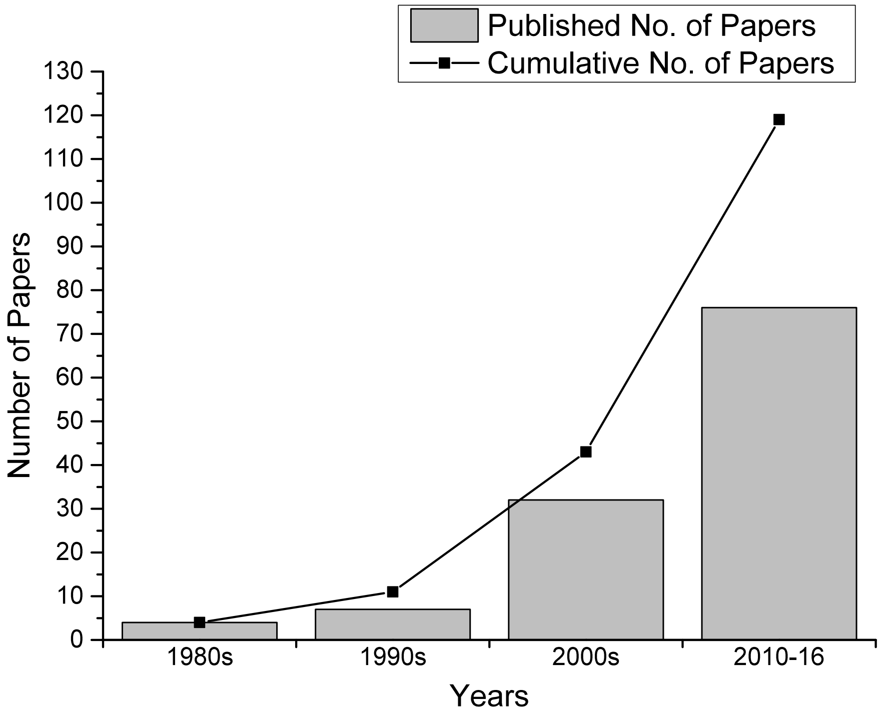


Figure 4.1: Number of Papers in the City Logistic Domain adapted and extended from (Kim et al. 2015)

ever."(Crainic et al. 2009a)

The research on and the availability of effective operations research methods for efficient operation of the CDCs and the intelligent coordination of their last-mile delivery vehicles is therefore quite limited and many research gaps exist. As noted before, a city logistic problem can be modeled as a Vehicle Routing Problem. For a VRP to be recognized as a City Logistics VRP, it must have one of the following attributes according (Taniguchi et al. 1999):

- Customers have pickup and delivery requests
- Customers are serviced within a specified delivery time window
- Traffic regulations impact the delivery fleet
- CLSP's objective is improving air or noise pollution
- Dynamic reaction of vehicles to newly available information

- CLSP interacts with the ITS

Dynamic reaction to changing environment or newly available information is quite common in vehicle routing. An overview is presented by Pillac et al. (2013). The changing environment in our research is the impact of the online traffic management system on travel times.

4.2 VRP with non static travel times

Non-static travel times are one of the major uncertainties for the tour planning in city logistics. The travel time varies because of different influence factors on the traffic. The travel time inside a city from point a to another point b could be influenced by traffic regulation, congestion, accidents, road works, traffic volume and road works (Ehmke and Mattfeld 2010). In general, travel times increase with a higher number of traffic participants. The amount of traffic participants changes with a certain predictability over the daytime. At night, the number of vehicles is small. In the morning, traffic increases because of the commuting traffic. Around midday, the traffic decreases and in the late afternoon, traffic increases again as commuter are driving back to their homes again. Towards night time, the traffic decreases again. This effect can be represented in a VRP as daytime-dependent travel times. Here, the day is split into parts of usually one hour time slots and each part has an associated travel time matrix. In city traffic, the travel times are, however, also affected by stochastic effects from accidents, congestion, short term road works or traffic regulation. This can be represented as a VRP with stochastic travel times. The work of this thesis includes stochastic and daytime dependent elements in its model. As with daytime-dependent travel times, when the travel time change, the complete matrix is substituted by another matrix. The number of available travel time matrices is also specified. The difference between our work and daytime-dependent travel times is that the change between matrices is not deterministic. The change is stochastic as the traffic management systems adjustments depend on the traffic or the air pollution level, which are already stochastic processes by themselves. The stochastic element has a significant influence on our problem, therefore we only briefly show related work in the field of VRPs with time-dependent travel times and focus more on VRPs with stochastic travel times. Furthermore, in Section 4.3, we clarify how the problem differentiates itself from existing green vehicle routing problems as both take emissions into account.

Table 4.1: Classification of VRP Literature with Stochastic Travel Times

Paper	Problem	Model Type	Anticipation	TT	TT Generation	Correlation	Emissions	Network
Laporte et al. (1992)	VRP	sc	impl.	st	art.	-	-	art.
Miller-Hooks and Mahmassani (2000)	VRP	sc & dc	impl.	st	art.	-	-	art.
Fu (2002)	DARP	sc	impl.	td & st	art.	-	-	art.
Kenyon and Morton (2003)	VRP	sc	expl.	st	art.	-	-	art.
Fleischmann et al. (2004)	VRPPD	dc	-	td	data	✓	-	art.
Taniguchi and Shimamoto (2004)	VRP	sc & dc	-	st	sim.	✓	-	art.
Ando and Taniguchi (2006)	VRPTW	sc	impl.	st	data	✓	✓	real
Van Woensel et al. (2008)	VRP	sc & dc	impl.	td & st	sim.	✓	-	art.
Xiang et al. (2008)	DARP	dc	-	td & st	art.	-	-	art.
Lecluyse et al. (2009)	VRP	sc	impl.	td & st	sim.	✓	-	art.
Li et al. (2010)	VRP	sc	impl.	st	art.	-	-	art.
Lorini et al. (2011)	VRPTW	dc	-	td & st	art-	-	-	art.
Yan et al. (2013)	VRP	dc	-	st	art.	-	-	art.
Ehmke and Campbell (2014)	VRPSC	sc & dc	impl.	td & st	data	✓	-	art.
Schilde et al. (2014)	DARP	dc	expl.	td & st	data	✓	-	real
Köster et al. (2015)	VRP	dc	-	td & st	art.	✓	-	art.
Köster et al. (2017a)	VRP	dc	expl.	td & st	art.	✓	✓	art.

4.2.1 Daytime-dependent Travel times

The vehicle routing problem with daytime-dependent travel times was introduced by Malandraki and Dial (1996). In this work, a function of daytime and distance results in an individual travel time. Since then, many authors proved the advantage of taking daytime-dependent travel times into account compared to routing with average travel time data (Van Woensel et al. 2008, Li et al. 2010, Ehmke et al. 2012). An important aspect of time-dependent travel time is the integration of real world Floating Car Data. Ehmke and Mattfeld (2010) presented a framework for processing FCD data into time-dependent travel times to enable the use of FCD in VRP models.

4.2.2 Stochastic Travel times

Table 4.1 shows a classification of VRP publications with stochastic travel times ordered by publication year. First, they are classified by problem type. Many of the presented papers investigate a standard delivery VRP, a VRP with specified customer time windows for the delivery (VRPTW) or a VRP with stochastic customer requests (VRPSC). Other authors examine the Dial-a-ride problem (DARP), where a company picks up customers and drops them off at another location for charge or the pick-up-and-delivery problem (VRPPD), where unlike the DARP the in-cargo time is not relevant. The category model type describes if a model is a static (sc) or a dynamic (dc) model. Furthermore, the model is classified if it anticipates the stochastic information and if this is done implicitly through inclusion in the solution method or explicitly through techniques like sampling. The travel times (TT) are classified in stochastic (st) and time-dependent (td) types and it is differentiated if they are generated from real world data (data), produced in a traffic simulation (sim.) or if the travel times are artificially (art.) generated. Additionally, it is categorized if correlation between multiple street segments exists, if emissions are regarded in the model and if a real world street geometry (real) is used or an artificial geometry (art.).

In 1992, Laporte et al. published the first work on a VRP that considered stochastic travel times (Laporte et al. 1992). The paper shows that a branch-and-cut approach can solve a static VRP to optimality for a pre-calculated a-priori tour with a target time for each customer while receiving penalty if the target time is not met. The stochastic travel times are revealed as the delivery tour is in progress. The tour's duration is then recalculated with the customer sequence of the a-priori tour and the stochastic travel times of each arc. This procedure is also used to evaluate the a-priori tours in this research. In 2003, Kenyon et al. compare routing with stochastic travel times to routing with mean travel times. Their research shows that the results when solving the stochastic VRP with a branch-and-cut scheme in an Monte Carlo sampling procedure is superior to the routing with mean travel times (Kenyon and Morton 2003). Other authors have calculated a-priori tours for stochastic travel times as well and integrated stochastic information implicitly in their solution method (Fu 2002, Ando and Taniguchi 2006, Lecluyse et al. 2009, Li et al. 2010) or explicitly through sampling Kenyon and Morton (2003). Some authors have compared static and dynamic solution method (Miller-Hooks and Mahmassani 2000, Van Woensel et al. 2008, Taniguchi and Shimamoto 2004). Some author used a dynamic model to re-optimize at every decision points to improve vehicle tours with newly available travel time information while disregarding stochastic effects in their decision process (Xiang et al. 2008, Lorini et al. 2011, Köster et al. 2015, Fleischmann et al. 2004). Other authors anticipate varying travel times in the dynamic model by explicitly considering future stochastic effects through sampling (Kenyon and Morton 2003, Schilde et al. 2014) or approximate dynamic programming (Köster et al. 2017a). Most authors generate their travel times artificially from a function or a distribution. To improve conformity of the model, Taniguchi and Shimamoto (2004) produces travel times from a traffic simulation. Van Woensel et al. (2008), Lecluyse et al. (2009) use a queuing approach to simulate near-realistic travel times. Ehmke and Campbell (2014) use time-dependent speed multipliers derived from FCD and combined them with a stochastic Burr XII Type 3 cdf distribution to simulate travel times. Historical travel times from FCD are used by Fleischmann et al. (2004), Ando and Taniguchi (2006), Schilde et al. (2014) to further improve the accuracy of their respective models. All simulated and real-world travel time approaches automatically assume a correlation of travel times between different street segments, only our previous work assumes a correlation for artificial travel times through stochastic matrices changes induced by traffic management measure effects (Köster et al. 2015, 2017a). Schilde et al. (2014) model congestion correlated as an area effect, which inflicts streets around a congestion point. Köster et al. (2015) show that traffic management measure affect travel times in the area around the measure in correlated fashion and show that it is beneficial for delivery routing to use information from an artificially modeled traffic-sensitive traffic management system. Köster et al. (2017a) consider an artificial environmental-sensitive traffic management system with three individual hot-spots and solve the associated model with an anticipatory approximate value iteration approach. In the computational experiments, the information level about the state of the traffic management system is varied and the results show that an efficient state space representation of the traffic management system status in the approximate value iteration approach is necessary to decrease delivery times significantly. For the modeling of the emissions at the hot-spots, real-world emission data was used. For most other authors, except for Ando and Taniguchi (2006), emissions were not part of the modeling, optimization or evaluation. In most cases, the transport geometry was created artificially, only Schilde et al. (2014) and Ando and Taniguchi (2006) integrated a real-world network into their model to increase validity of their models.

4.3 Green Vehicle Routing

The field of green vehicle routing has seen a sharp increase of research papers in last five years. Their objective is to minimize the emission production of the delivery fleet. This is either done by using emissions as the objective in the optimization of the route planing, wherefore each arc receives a corresponding emission production value (Figliozzi 2010, Eglese and Bektas 2014, Ehmke et al. 2016), or by optimizing vehicle speeds in traffic (Bektaş and Laporte 2011, Demir et al. 2014, Franceschetti et al. 2013). In this work, the objective for the city logistics service provider is to minimize costs from the delivery and not the emissions. Nevertheless, we show that traffic management information does not only reduce routing costs for a CLSP, but also emissions at critical emission hot-spots for the traffic management system. The literature review reveals that traffic management systems and their relationship to logistics is not studied in-depth in the research community yet. Therefore, the background information about traffic management systems and their potential contact points to logistics is given in the following chapter.

Chapter 5

Traffic Management

Road traffic needs organization of its traffic flow to prevent accidents. Behavior rules, road signs and pavement markings or the extensive use of traffic signals in urban areas helped to improve the management of traffic by making it safer and more efficient (Dantas and Friedrich 2014). This is defined as *traffic management* and is in essence a tool for the municipality to improve traffic conditions through sets of short-, medium- and long-term actions (FGSV 2011). The term traffic management is used in context of air, water, railway and road traffic. For this thesis, the term is used for the management of road traffic.

5.1 Traffic Management Goals

The traffic management goal is to improve traffic safety and efficiency by a goal-oriented handling of traffic supply and traffic demand. The traffic flow quality usually increases if less vehicles are on the road. To achieve this, the traffic management tries to reduce the traffic demand by changing the behavior of the population to prevent unnecessary mobility and promote the use of public transportation for a better modal shift and by increasing the occupancy rate of vehicles for less and a better spatial and temporal distribution of the traffic. The traffic supply is influenced by increasing road utilization and capacities and decreasing disturbances in the traffic flows. According to Schnabel and Lohse (2011a), the objectives of road traffic management are:

- Enable the mobility of the population

- Interconnect different modes of transportation
- Influence the behavior of traffic participants through information
- Decrease traffic related pollution production
- Increase traffic safety
- Optimize traffic flow

Many of these aspects are especially important in urban areas and on highways, because here the traffic load is higher and more volatile than in rural areas. The most important task of traffic management is to guarantee that individual and freight transportation is possible. If this is secured, the traffic management works on improving all travel modes. The term transport mode is used to distinguish different ways to perform the movement. Popular in individual transportation is traveling by road in a car or by public transport in a bus or train. The modal split represent the percental usage rates of all modes. For the traffic management one goal is to improve the modal split of public transport as this reduces the number of cars in traffic and is often done by prioritizing public transports in traffic or by improving the interconnection between different transport modes. That simplifies trips that require two different transportation modes. Traffic participants can adapt their travel plans with information about traffic condition and public transport to avoid congested areas. This is good for the travelers, who arrive faster at their respective destinations, and for the traffic management as further traffic burdens on congested areas are lowered. Increasing the air quality through decreasing traffic related GHG production is becoming more important for traffic management with the increased knowledge about the related human health issues. Accident prevention and decreasing the severity of accidents has a long history in traffic management. Today's focus of traffic management is often on increasing the utilization of roads and improving the traffic infrastructure. This can be done with strategic long term projects like new roads or medium and short term implementation of traffic management actions (Schnabel and Lohse 2011a,b).

5.2 Traffic Management Actions

Actions are defined measures by the traffic management to interfere with traffic for a defined purpose. This is achieved with changes to the properties of the infrastructure. A measure allows or forbids a traffic movement or impacts the capacity on affected street link. The capacity in return influences the traffic flow, which together implies a certain travel speed and therefore also a certain travel time on that street segment. Often many individual actions are combined to achieve a greater effect for the selected intention for changing the current traffic flows for safety, environmental or efficiency reasons (Brockfeld et al. 2001, Celikkaya et al. 2016). This is called a $traffic\ strategy$. The traffic strategies are preplanned, because of the number of possible actions. Additionally, many traffic conditions like for example the monday morning traffic jam in a specific city area are reoccurring inside a city. This allows the development of the best possible measure bundle for that situation. The actions of the traffic management consist of controllable traffic infrastructure, which can be classified into the following categories (FGSV 2003):

- Increasing/Decreasing capacity through traffic signal control
- Allow temporary lanes
- Speed limits
- Variable message signs
- Ramp metering
- Overtaking restrictions
- Toll systems
- Low Emission Zones

Traffic light control programs at intersections have a high influence on city traffic flows (Brockfeld et al. 2001). This is enabled by the high number of traffic lights in cities and their ability to completely stop traffic. Consequently, they have a high impact on travel times in cities and a lot of research has been conducted on optimizing intersection traffic lights. The control lights can be varied in the sequence and composition of the phases and in cycle times. Traffic light programs can have a complete fixed program, a daytime dependent change of programs or can be adjusted dynamically depending on the current traffic load. Many intersections controllers work isolated from others, but it is also possible to coordinate adjacent intersections to allow coordinated green bands to accelerate traffic flow in a direction significantly (Pohlmann 2011). Traffic lights are, however, bound to constraints, when prioritizing one direction, other directions will be negatively affected. Traffic lights can use long red and only short green phases to restrict access to reduce further pollution or congestion in certain city areas. Temporary lane control, which suspends or allows traffic lanes on a road to a direction, is not feasible at many locations, but can have a positive effect on traffic flows. Speed limits can slow traffic flows into an area to increase security or reduce vehicle emissions. Message signs can be installed nearly everywhere and give traffic information and routing recommendations to traffic participants. This and other actions like ramp metering and overtaking restrictions are especially introduced for entering and on highways. Toll systems and low emission zones are a traffic management measure to force traffic participants to partly carry the cost of the infrastructure and to reduce traffic and congestion in defined areas.

5.3 Dynamic Traffic Management

A traffic management that reacts instantly in real-time through the coordination of actions from section 5.2 for best possible transportation is defined as a *Dynamic Traffic Management* (FGSV 2003). Modern communication and processor technologies allow the dynamic adaption of the traffic management actions and to the evaluate what the best traffic strategy for the current traffic load or environmental air pollution is (Celikkaya et al. 2016). These dynamically and automatically reacting traffic management systems are a part of the $Intelligent\ Traffic\ Mangement$ *Systems* (ITS) and as of 2016 are used in practice in many cities worldwide. Traffic Management systems that dynamically react to the current traffic load are around for more than 30 years for the control of traffic lights for isolated single intersections and help to keep the traffic moving despite a growing number of vehicles. Today, dynamic traffic management systems do not only optimize signal phases for a single intersection, but for adjacent intersections or even a complete network. Environmental and traffic dependent traffic management systems constantly monitor the traffic and air pollution through sensors and the collected real-time data is the foundation for efficient operation. The data is collected via sensors like cameras, induction loops, infrared sensors, Floating Car Data (FCD) sources and by air pollution measurements and allow the traffic management the supervision of the traffic and air pollution condition.

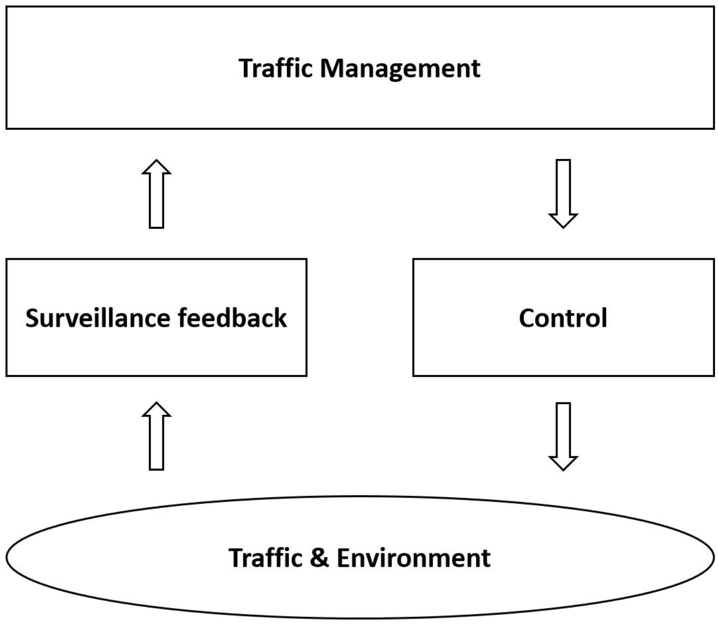


Figure 5.1: Decision Process of Traffic Management adapted from Yang and Koutsopoulos (1996)

Figure 5.1 shows the continuous decision process of a dynamic traffic management system. The traffic and environmental state, which represents the current situation in traffic network is continuously observed and additional information like traffic or pollution forecasts are used to evaluate the state of transport system. If the evaluation shows that a better or safer traffic strategy exists for the current state, the traffic management system enables the actions according to the new traffic strategy through modern technologies and communication. The traffic then responds to the infrastructure attributes decision and transitions into the next state (Yang and Koutsopoulos 1996).

5.4 Dynamic Traffic-Responsive Traffic Management Systems

The development of dynamic traffic management system was started in 1973 with the Split, Cycle and Offset Optimization Technique (SPLIT) in Britain and was taken into operation in 1979 in Glasgow, Scotland (Hunt et al. 1981, 1982). The main idea was to adapt traffic signal plans dynamically to the current load of traffic for each

Table 5.1: EU Air Quality Standards (adapted from Agency (2016))

Pollutant	Limit	Avg. period	Permitted annual exceedences
Fine particles (PM2.5)	25 $\mu g/m^3$	1 year	n/a
Fine particles (PM10)	50 $\mu g/m^3$	24 hours	35
	40 $\mu g/m^3$	1 year	n/a
Sulphur dioxide (SO2)	350 $\mu g/m^3$	1 hours	24
	125 $\mu g/m^3$	24 hours	3
Nitrogen dioxide (NO2)	200 $\mu g/m^3$	1 hour	18
	40 $\mu g/m^3$	1 year	n/a
Lead (Pb)	0.5 $\mu g/m^3$	1 year	n/a
Carbon monoxide (CO)	10 mg/m^3	8 hour	n/a
Benzene	5 $\mu g/m^3$	1 year	n/a
Ozone	120 $\mu g/m^3$	8 hours	25 over 3 years
Arsenic (As)	6 ng/m^3	1 year	n/a
Cadmium (Cd)	5 ng/m^3	1 year	n/a
Nickel (Ni)	20 ng/m^3	1 year	n/a

intersection. This is defined as a traffic responsive approach as the controller reacts purely on traffic loads. The Sydney Coordinated Adaptive Traffic System (SCATS) is in operation since 1982 and its further developed methodology is implemented in multiple Australian and Asian cities today (Pohlmann 2011). Both systems are widely used in today's world and calculate the signal plans in a centralized system architecture for each intersection individually without the consideration of other signal plans in the network (Pohlmann 2011). The Balancing Adaptive Network Control Method (BALANCE) was developed at the Technische Universität München in two European research projects (Friedrich 1999). It considers a complete city network and has a three level architecture to be robust against failures. It is, for example, used in Ingolstadt, Germany and uses green bands to reduce waiting times at intersection by up to 20% (PTV 2012). These systems and others like OPAC, Rhodes and TUC have shown to be able to influence traffic positively and instantly through dynamic adaption of the infrastructure (Dantas and Friedrich 2014).

5.5 Dynamic Environmental-Sensitive Traffic Management Systems

Next to the increased challenge of organizing traffic more efficiently in cities, air pollution is also becoming an issue for traffic management. This is especially true in

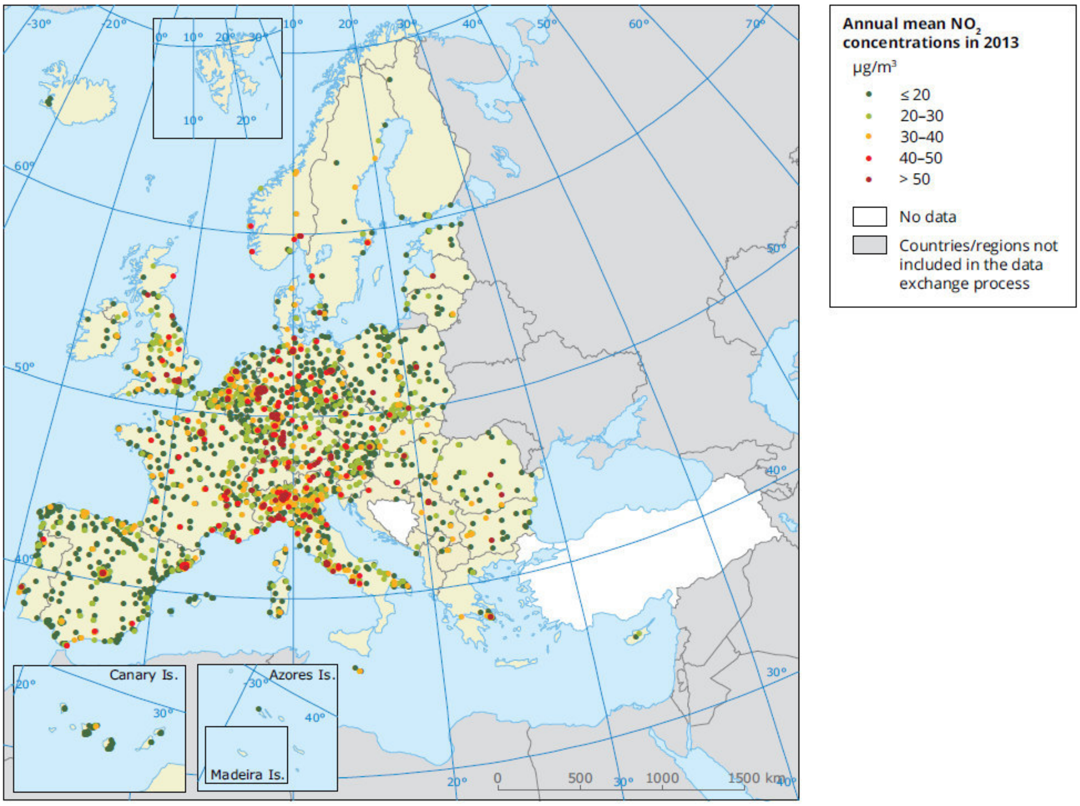


Figure 5.2: Annual mean NO_2 Concentrations in EU Cities (Agency 2015a)

Europe, since the European Union (EU) passed the regulation 2008/50/EC, which limits the averaged air pollution in defined time periods (EU 2008). In the regulation limits, for short term violations for extremely high pollution values and for long term violations for many GHG and PM_x exist as seen in Table 5.1. Many European city exceed the regulation of short term violations of 8 or 24 hours multiple times in multiple categories as well as the long term annual pollution averages (Agency 2015a). The severity of air pollution violation can be seen in Figure 5.2, which shows the annual average NO_2 pollution of European cities in relation to the annual restriction limit of 40 $\mu g/m^3$ from the EU regulation. It can be discovered that the air pollution is especially bad in northern Italy and western Germany, but in essence, every capital of the shown area has dangerous air pollution concentrations. According to the European Environment Agency, up to 31 % of the EU urban population were exposed to high NO_2 and up to 42 % to PM_{10} values. This poses as a health threat for urban residents and is a major challenge for city authorities and their traffic planners as traffic is a significant contributor to air pollution problems. Not complying or completely ignoring the air pollution regulations is not an option for cities as it can results in hefty EU fines. Many cities have installed static traffic regulations to reduce the problem in the inner-city. A common regulation was for example the setup of low-emission zones, which can only be entered if the traffic participant's vehicle followed determined exhaustion limits. Some cities have implemented dynamic traffic management actions against high air pollution. Rome and Milan for example temporally banned cars from the road after experiencing high air pollution (BBC 2015). Paris has the "Paris Emergency Scheme", which in essence halves the traffic with alternating odd-even numberplate drive permissions (CLARS 2016). These schemes do however hinder the mobility of the cities' residents tremendously and might not be feasible and accepted everywhere. The German cities Braunschweig and Potsdam have installed dynamic environmental-sensitive traffic management systems (Bellis et al. 2010, Ministerium für Umwelt 2016). These systems try to reduce the emission production of vehicles as much as possible while keeping the traffic as efficient as possible (Boltze and Kohoutek 2010). Both cities have identified air pollution hot-spots, where the NO_2 and PM_{10} pollution is especially high and above the EU limits. For all hot-spots, an extensive analysis of traffic demand and possible traffic management actions were made with simulation models. Results show a reduction of NO_2 in certain conditions by up to 25% (Bellis et al. 2012). The traffic management actions are not implemented only in the vicinity of the hot-spot, but also reasonably far to redirect traffic to other route options. This limits access to the hot-spot areas. At the same time, traffic inside a hot-spot area is accelerated for a reduced pollution production by coordinating traffic signals for a green band. In practice, these systems have shown to decrease noise and pollution levels while not completely limiting access to city areas at polluted times through influencing traffic flows dynamically (Potsdam 2016, Celikkaya et al. 2016).

5.6 Environmental Impact of Urban Transport Systems

Transportation is a major contributor to air pollution problems of many cities world-wide. Air pollution should be considered more critically, because it is responsible for global warming and human health problems. Responsible for much of the air pollution are the Greenhouse gases (GHG). GHG are formed through the use of fossil fuels and they are therefore associated with classic combustion engines in vehicles. Better known GHG are for example Carbon Dioxide CO_2 and Nitrogen Dioxide NO_2. Particular Matter PM_x is not a GHG, but also dangerous to humans. PM_x are small particles in μm range and their size is quantified in intervals. Like GHG, they can be produced through fossil fueled transportation and contributes to transportation related air pollution.

Of the total Green House Gas production, transportation is the second largest emitting sector and accounts for 26%. It trails only the electricity sector, which burns a huge amount of fossil fuels like coal and is responsible for 30% (Agency 2015b). Transportation is however more responsible for air pollution in cities than the electrical sector as it emits more in the urban environment. Of the complete road traffic, freight transportation accounts only for about 20% of the CO_2 emissions of all transportation related actives, but is responsible for about 50% of the NO_x and nearly 40% of the PM_x emissions (Inventory 2005a,b). Consequently, the freight sector has a significant impact on the air pollution in cities and health of its residents. The GHG production per kilometer of a vehicle depends on the amount of used fuel, the fuel type and how it is combusted, the aerodynamic drag of the vehicle, vehicle weight, driving behavior and traffic conditions (Kellner 2016). Many freight companies try to greenwash their image through compensation projects like carbon credits/offsets. The major parcel shipping companies (DHL, UPS, DPD and Hermes) in Germany all have such a program. The programs are quite similar and suggest GHG neutral shipping coupled with a special projects like E-mobility for a small part of the delivery fleet (DPD 2017, Hermes 2017, Ltd 2012, Service 2016). In the operational planning, CEP services often ignore emissions and focus on reducing cost and improving efficiency and service level. Reason for this are the immense cost pressure, the fact that many emissions can not be avoided anyway and costs through pollution are an external cost for the human society, which transportation companies do not cover.

For residents, the polluted air can result in significant health problems like chronic heart disease, lung cancer, respiratory infections in children, aggregation of other heart and lung diseases or asthmatic attacks (Brunekreef and Holgate 2002, Kampa and Castanas 2008). The worst air pollution arises in Asia, especially in India and China, where as of 2017 many ecological-friendly standards of the western world are not applied (NEWS 2016, 2017). Residents are even advised to stay at home on extremely polluted days. But air pollution problems also happens frequently in the western world. While transportation technology has improved over the last decades by making individual vehicles more GHG friendly, the demand for transportation has grown even stronger. This often results in traffic congestion, which further amplifies the problem and is a significant contributor to city air pollution. Forecasts for the western world show that a further increase in congestion is expected (McKinnon et al. 2009). Until GHG neutral transportation is invented, the trend in many countries is to make efforts to improve air quality through regulations. They either disallow certain "dirty" technologies and behaviors or try to reduce a city's congestion through an improved traffic management.

5.7 Modeling Traffic and Traffic Management in a VRP

Travel times on individual streets and between CLSP customers are significantly impacted by the traffic management actions that are bundled into the traffic strategies as described in Section 5.2. The strategy accelerates traffic in one area, but often limits traffic flows in another area due to the nature of traffic and traffic lights. This has an impact on the travel times on individual street segments and the customer-customer connection, which are defined as a link and are constructed from single street segments. Consequently, travel times on street segments can have a similar behavior, however, it can also happen that a link effect is negated as it can be influenced by a traffic flow acceleration in one area and a slow down in another area. In this section, we show the impacts that effect travel times on a link level. Therefore, we first present time-dependent and stochastic travel times, before we illustrate the effect of traffic management strategies on travel times.

Stochastic travel times for single street segments are represented by stochastic distributions. This can for example be a Burr III Type XII or Gamma distribution (Susilawati et al. 2013). For travel time of customer-customer links, these distributions needs to be aggregated unless each street segment's stochastic effect is realized individually in a model each time, which depending on model-size can have a high computational burden. With an aggregation, a closed form-distribution can not be obtained (Groß et al. 2015). A distribution is usually modeled around an expected mean value μ and a standard deviation value for the link. A travel time τ_l for a link l in a model is created from the mean value μ_l and a noise distribution ϵ_l as

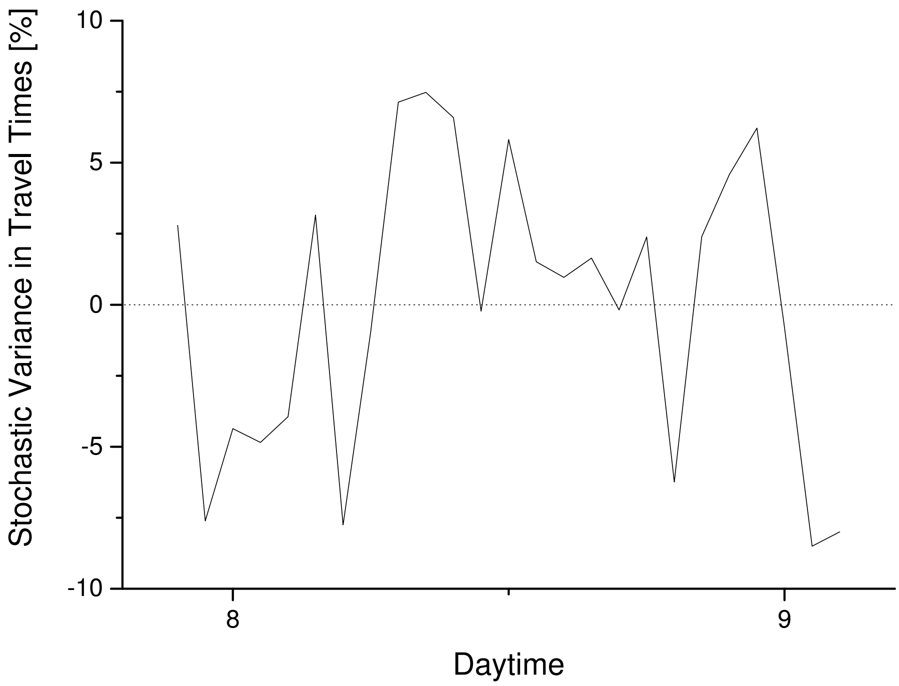


Figure 5.3: Exemplary Effect of Stochasticity on Travel Times for a Link (adapted from Köster et al. (2015))

seen in Equation 5.1. The noise value is drawn from the standard deviation with an expected value of zero as seen in Figure 5.3.

$$\tau_l = \mu_l \times (1 + \epsilon_l) \tag{5.1}$$

Travel times are dependent on the traffic volume. The traffic volume is constituted by the number of vehicles that are using the road and it follows a daytime-dependent pattern. Especially during commuting hours, the traffic flows increase significantly resulting in prolongued travel times. Time-dependent travel time data is often structured in time intervals of one hour in which a deterministic travel time for each street segment exists. The time intervals are described by time-indices $t \in \{0, ..., t_{\max}\}$ as depicted in Equation 5.2 and are modeled from real-world data as described in Section 3.1 or as a function of daytime.

$$\tau_l(t) = \mu_l(t) \text{ with } t = \{0, ..., t_{\max}\} \tag{5.2}$$

When Equation 5.1 and Equation 5.2 are combined in Equation 5.3, it enables

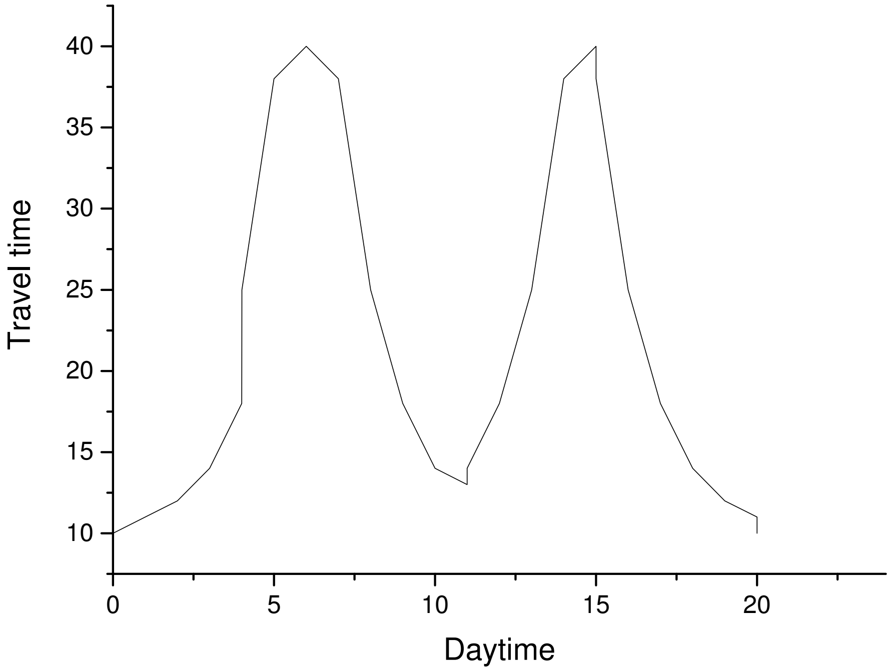


Figure 5.4: Exemplary Time-dependent Travel Times for a Link (adapted from Köster et al. (2015))

stochastic and time-dependent travel times for a link. For each point in time t, a travel time $\mu_l(t)$ is influenced by a time-dependent noise-distribution $\epsilon_l(t)$. The distribution of $\epsilon_l(t)$ varies over the day as well.

$$\tau_l(t) = \mu_l(t) \times (1 + \epsilon_l(t)) \text{ with } t = \{0, ..., t_{\max}\} \tag{5.3}$$

Traffic management strategies $T_1, \ldots, T_n$ can be defined as sets of on infrastructure actions from traffic management decisions. Every measure specifically impacts link's travel times by increasing or decreasing the street capacity by a certain factor f_i. This traffic management traffic influencing factor is exemplarily shown in Figure 5.5. Here, different strategies are applied over the course of the day. During commuting hours, the link capacity is increased to allow a fluent traffic for example through prolonged green times. In the case of the example, orthogonal roads are negatively affected through prolonged red times. In the middle of the day and in the night, green times are distributed more fairly.

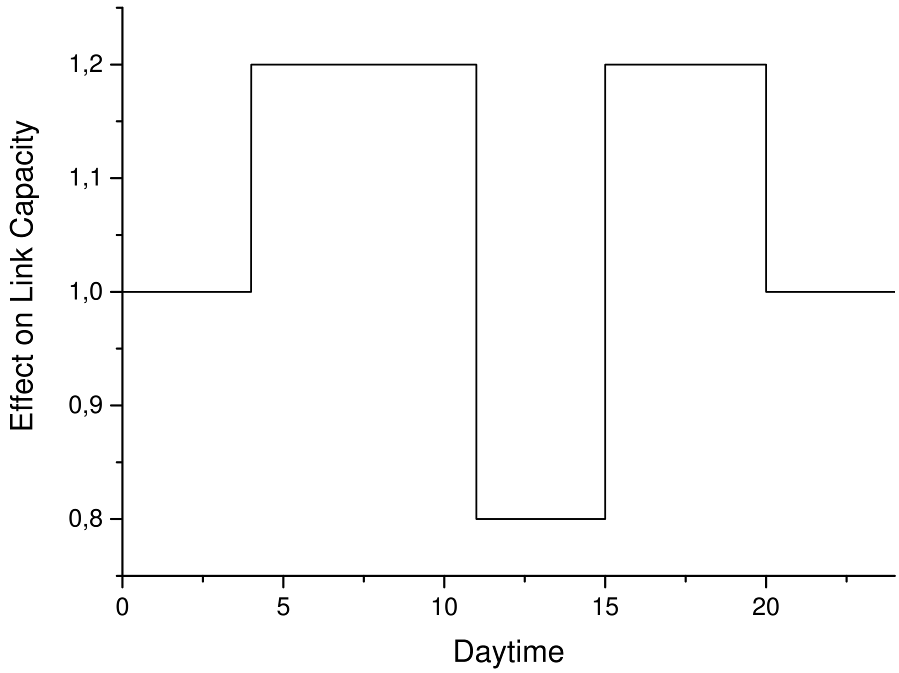


Figure 5.5: Exemplary Effect of TM on Travel Times for a Link (adapted from Köster et al. (2015))

The factor $\delta_l(T_n)$ represents the influence factor for link l for strategy T_n. The resulting travel time $\tau_l(t)$ then also depends on the active strategy T^n. This influence of T_n is combined with influence of the stochastic and time-dependent travel time impact in Equation 5.4.

$$\tau_l(t) = \delta_l(T^n) \times \mu_l(t) \times (1 + \epsilon_l) \text{ with } t = \{0, ..., t_{\max}\}, T^n = \{T_1, ..., T_n\} \tag{5.4}$$

Consequently, the derived travel time for a customer-customer link depends on the active strategy T^n, the daytime t and the stochastic noise variation ϵ (Köster et al. 2015).

Part II

Case Study

Chapter 6

Logistics and Traffic Management Systems

In the Part II of this thesis, we first motivate a cooperation between logistics and traffic management in Chapter 6 and describe the need for optimization approaches for solving the derived Dynamic Vehicle Routing Problem with Stochastic Matrix Changes. In Chapter 7, we present the case study for the experiments on an environmental-sensitive traffic management system as the source for travel time matrix changes and a city logistics service provider for two urban delivery problems. Therefore, a two-layered model architecture is presented in Chapter 8 and the solution approaches are presented in Chapter 9.

6.1 Cooperation between Logistics and Traffic Management

Urban traffic is difficult to predict and for city logistics service providers this leads to planning problems when determining delivery routes as urban travel times are volatile. Sources for the uncertainty and volatility of travel times are congestions, varying road conditions, traffic management actions, rush hour effects and accidents (Ehmke and Mattfeld 2010). In general, more vehicles and disturbances in traffic lead to higher and less certain travel times. As a results, delivery routes of a CLSP are often less efficient as vehicles might not take the fastest route between stops in the tour or simply have an inefficient customer delivery sequence. The traffic management impacts traffic with its traffic strategy through accelerating or slowing specified traffic flows. This does not only impact the travel time between two customer locations, where the route is inflicted by traffic management actions, it can also change the composition of the route itself. A delivery truck could for example lose a significant amount of time traveling a slower route between two customers. This could result in having to pay the truck driver extra hours or to a higher fuel consumption by the delivery truck. Even though the traffic strategies of the traffic management impact traffic and could potentially be of value to the delivery planning systems to improve accuracy and efficiency of the tour plans, the traffic strategies are not communicated. The idea of the cooperation is that the CLSP can improve their operational planning through information about active traffic management actions. Information about static and long-term traffic actions would however not be of high interest for a CLSP as this information will get known eventually anyway. Information about dynamic traffic management actions on the other hand either from traffic-responsive or environmental-sensitive traffic management system would be of particular interest for a CLSP as they change the traffic situation instantly on a short-term basis. In return, the CLSP could either pay through a contractual relationship for the information or avoid congested/polluted area, which would be a significant benefit for the traffic management. This could be planned happen as a byproduct through optimized routes by the CLSP.

As of 2017, no such cooperation between a logistics company and traffic management is in practice. This has different reasons from both parties. Most important, the potential benefits for each parties are not known so far. Furthermore, there is a missing technical standard for the data and platform to distribute information. The traffic management could also not want to share information as they fear they could be critiqued for their decision on traffic strategies and that some user would exploit the traffic management actions, which would result in more congestion/pollution. For the CLSP the question is which traffic strategy results in which travel time change on which street link and how this information could be incorporated into their planning system. The complexity of a successful implementation is especially high if the traffic management includes a forecast. In order to participate in a cooperation, the CLSP must also have an economic benefit, which would arise if the saved costs from more efficient delivery tours outweigh all costs of implementing a planning system with traffic management information.

Having an efficient urban freight transportation is critical for the CLSP. Cities continue to grow and at one point, the current conventional planning methods are becoming uneconomical. Therefore in this thesis, the cooperation is analyzed in a case study to investigate the value of a cooperation for both partners. We use a case, where the CLSP has no information as a reference for the current state of the art in CLSP industry. Furthermore, the traffic management produces an emission forecast, which could also be provided to the CLSP as the emission trajectories dictate the traffic strategy. For our experiments, we can differentiate between three cooperation levels:

- No information from the traffic management
- Current traffic management information
- Current traffic management information and emission forecast

The case study consist of the environmental-sensitive traffic management system in Braunschweig, Germany and two different CLSP problems with slightly different tasks. The first task is a delivery problem where all customers are known in the beginning of the day. The second task is a pick-up problem where only a fraction of the customers are known in the beginning of the day and the remaining customers request a pick-up dynamically during the day. The problems are modeled as Vehicle Routing Problems and can be defined as *dynamic vehicle routing problem with stochastic changes of travel time matrices*. In each of the problem, the goods are first distributed between the vehicles of the fleet. Then, the dispatcher routes each vehicle individually to its customers. While the vehicles deliver goods to their customers, the traffic strategy, which is based on actual emission behavior from a dataset, changes. A traffic strategy change results in different travel times between the destinations of the vehicles, which are collected in a travel time matrix. The dispatcher can dynamically adapt the routes of the vehicles. The objective is to minimize the total travel times for all deliveries of the fleet. For the different cooperation levels, we use different routing policies to maximize the benefit from the additional information. We test the policies for different case study instance settings by varying the fleet size and the traffic management impact on traffic speeds. Our contributions are as follows. This thesis is the first to analyze if and how a cooperation between traffic management and CLSP can lead to a benefit for both partners. The presentation of the DVRPMC provides a new dynamic routing problem which considers emissions and traffic management. Furthermore, we provide a Markov decision process model, which incorporates stochastic *correlated* travel times. This is a feature that is generally neglected in the literature.

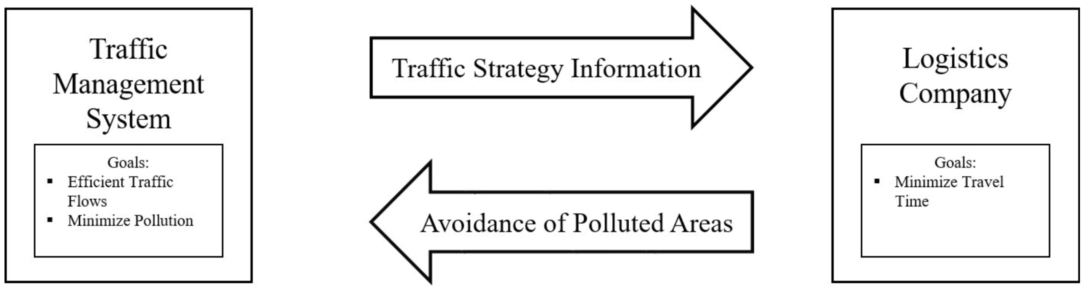


Figure 6.1: Cooperation between TMS and CLSP

For a cooperation to function between two partners, each needs a benefit towards their own goals. Figure 6.1 shows such a case for the problem. The traffic management system provides information about its traffic strategy to the CLSP, who can integrate this information into its tour planning and avoids problematic areas for the traffic management in return. It is, however, questionable if the tour durations can be improved and if the avoidance of problematic areas is significantly with this information. To analyze this, we vary the degree of cooperation with the three traffic management information level for the CLSP. We use a case, where the CLSP has no information as a reference. Furthermore, the traffic management also produces an emission forecast, which could also be provided to the CLSP as the emission trajectories dictate the traffic strategy. Furthermore, we use different routing solution techniques for the CLSP planning to evaluate for which technique the information is most beneficial. Therefore, we concentrate on the following three cases, which are explained in more detail in the following sections:

- A-priori routing
- Re-optimization with current traffic management information
- Re-optimization with current traffic management information and anticipation

In the last section of this chapter, we present how the traffic management can benefit from a cooperation through traffic management information adapted tour plans of the city logistics service provider.

6.2 Introductional Example

In this exemplary parcel delivery planning situation, a CLSP has to serve customers with deliveries in an urban environment. Because of the highly competitive nature of the parcel delivery industry, it is important to reduce costs from deliveries, which are influenced by uncertainties. In this case, the objective is to minimize delivery times as the working costs of the delivery truck drivers are often the major cost aspect in last mile deliveries. In the presented example in the following sections, the travel times vary because of traffic management decisions. The planning problem is modeled as the DVRPMC. In general, the networks of VRPs consist of edges between each of their nodes, which are the customers and the depot. The data for case study of the environmental-sensitive traffic management system is based on the real-world city transport network of Braunschweig, which also includes many street segments and intersections as nodes. In this chapter, we show how the VRP network is derived from an exemplary city network.

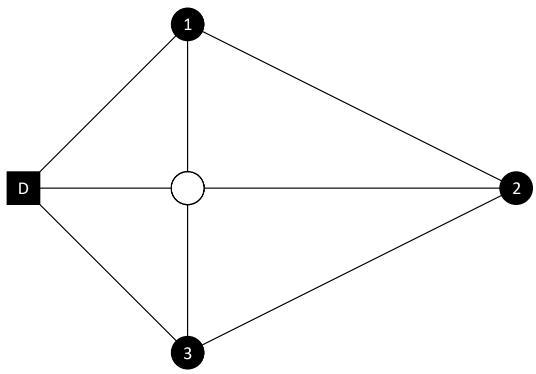
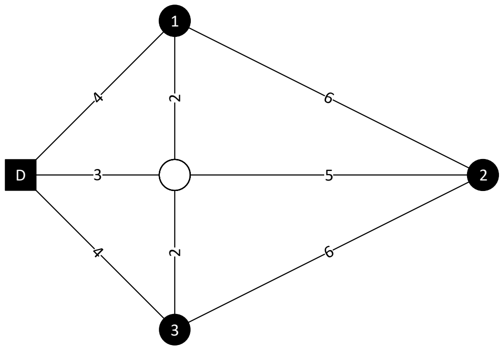
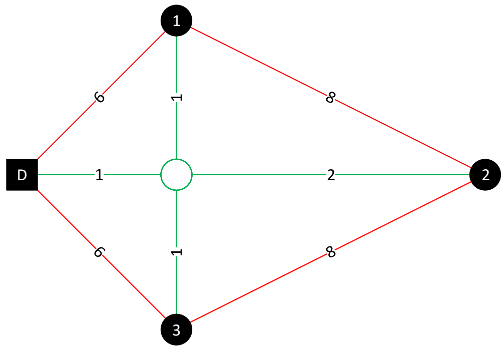


Figure 6.2: Exemplary City Network with One Depot, Three Customers and One Intersection

Figure 6.2 shows the exemplary city network for the delivery planning situation with five nodes. The three circle-formed nodes represent the customers of the CLSP. The quadratic node represents the depot and the small circle shape in the middle of the map represents an intersection, which is also a node in the network. The black lines represent undirected edges between the nodes. Notably in this example, for each customer-customer connection, multiple route path options exist. Either the vehicle can travel through the intersection node in the middle and then to next destination or use the directly connected path on the outside.



(a) Travel Times with Traffic Management Strategy One

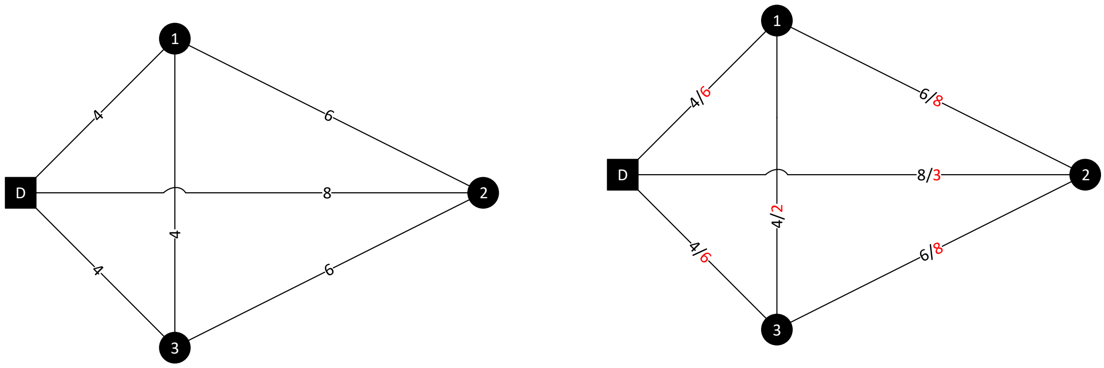


(b) Travel Times with Traffic Management Strategy Two

Figure 6.3: Travel Times in the Exemplary City Network

Each edge has a weight, which describes the travel duration it takes to traverse from the start node of the edge to the end node. Each edge weight is affected by a traffic management strategy. In our example, the travel time only depends on the traffic strategy and each edge has a deterministic weight for each traffic strategy. If the traffic strategy changes the complete set of edge weights is substituted. The transition between the traffic strategies is enforced by the traffic management and outside the decision scope of the CLSP. The traffic management enforced travel time matrix changes are stochastic as they react on stochastic effects like emissions and traffic. For this introductional example, two different traffic management strategies exist as seen in Figure 6.3a and 6.3b. In this case, strategy one implies the standard traffic actions and strategy two implies special actions to slow traffic on the outside edges. The two strategies differ significantly. As an example, we analyze the customer-customer connection from customer two to customer three. In strategy one, as seen in 6.3a, the fastest connection is the directly connected edge with a travel time of $t_{2\text{ - }3}^{\text{strategy one}} = 6$. For strategy two, the fastest connection goes through the intersection node with a travel time of $t_{2\text{ - }3}^{\text{strategy two}} = 3$.

The objective of CLSP is to serve all three customers (1,2 and 3) while using the transport geometry. In this case, the dispatcher decides how the customers will be sequenced in the delivery tour of the vehicle. Each tour starts and ends at the CLSP depot (D), because it acts as a regional hub where delivery goods are incoming and have to be delivered over the last mile. The problem is modeled as a VRP.



(a) VRP Network with Traffic Management Strategy One

(b) Travel Times of the VRP Network with Traffic Management Strategy One for different Cooperation levels

Figure 6.4: Derived VRP Network with Travel Times in Exemplary Network

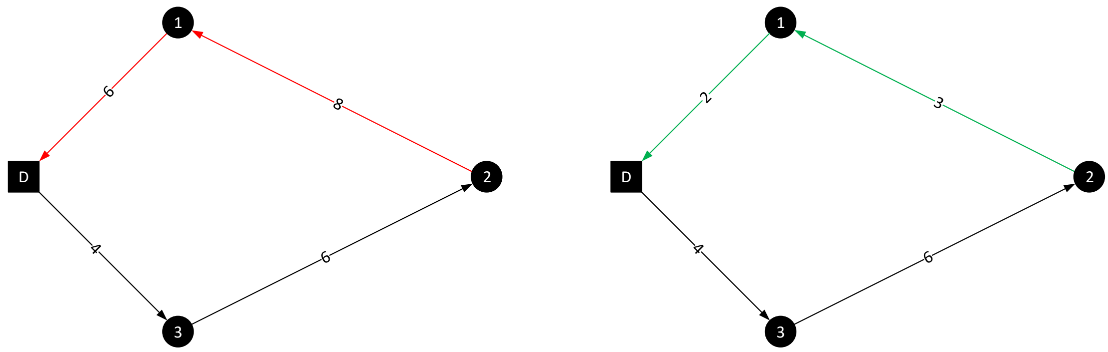
The network is aggregated to ”important” nodes” (the depot and the customers) for decision-making as seen for the traffic strategy one in 6.4a. In a VRP model, the intersection node is therefore neglected. However, this does not mean that this node is simply deleted. The edges in the VRP model are only aggregated representations of routes between the two ”important” nodes that include multiple street segments. The travel times of the VRP edges are derived from the original city network seen in Figure 6.3a and calculated with shortest-path algorithms for the VRP model. The visualization of this is shown as a network in Figure 6.4a. When deciding for a certain sequence in the VRP, this decisions therefore implicitly implies a certain path in the city network.

For example when strategy one is active, every decision to travel between two customers would imply using the outside edges and not the way through intersection node. This becomes interesting if a CLSP's dispatcher has no information about the active traffic strategy as it as the current state of the art where no cooperation between CLSP and traffic management is in place. Here, we have to differentiate between decision making and actual vehicle transition between nodes. As an example, a dispatcher plans the delivery tour for the vehicle with the travel times from traffic strategy one. However, no cooperation is in place and actually strategy two is currently active. This could mean that the dispatcher could route the vehicle not only in an inefficient customer sequence, but also sends the vehicle the longer route path between two nodes of the VRP network as he expects it to be faster. For example, the dispatcher expects a travel time of $t_{1\text{ - }2}^{\text{strategy one}} = 4$ for traveling from customer one to customer two when traffic strategy one is active. This implies the use of the outside edges of the city transport network. However, as traffic strategy two is actually active, the travel time increases to $t^{\text{strategy one}}_{\text{detour way: 1 - 2}}$ =6. These properties of an edge in the VRP network are visualized in Graph 6.4b in a case where traffic strategy one is used for the CLSP planning. If strategy one is indeed active the black colored travel time can be used for the vehicle transition to the next node. If strategy two is active, the vehicle transitions to the next node with the redly colored travel time edge weights. Notably as seen in the graph, it is also possible that the travel time of some edges decrease (i.e. edge weight between node 1 and node 3). However, when planning with many customers it is unlikely that these edges are used. Consequently, a cooperation that allows information transfer about the traffic strategy therefore should enable the dispatcher to plan routes more efficiently.

6.3 A-priori and Dynamic Re-Optimization

For the CLSP, it is a question how to use and integrate traffic management information about the active traffic strategy from a cooperation, which regulates the current travel time matrix, into tour planning. An option for the vehicle routing are a-priori tours. Here, the complete tour with its customer delivery sequence is determined before the tour actually starts. This technique has several advantages. First, the tour must only be calculated once and second, it can be transferred to the delivery vehicle's navigation system or by paper list to the driver at the depot quite easily. Therefore, the costs are small compared to other techniques like dynamic re-optimization. However, a major drawback is that a-priori tours are static, which means that once the vehicle starts its delivery tour, the sequence of the customers can not be adjusted. With non-deterministic travel times, this could result in significantly longer tour durations as the vehicle can not react to changed travel times. A solution for this is dynamic re-optimization, where at decision points, (e.g. in this example at customer locations after a successful delivery) the delivery sequence and the corresponding paths are reevaluated. Both, the sequence and paths can be adjusted if this would result in a faster tour based on the current knowledge of travel times. In practice, this is associated with higher fixed costs because it requires more technology. The costs can, however, be recovered through faster tours, which reduce the variable costs of the delivery tours.

To show the benefit of a dynamic re-optimization compared to an a-priori so-



(a) A-priori Tour

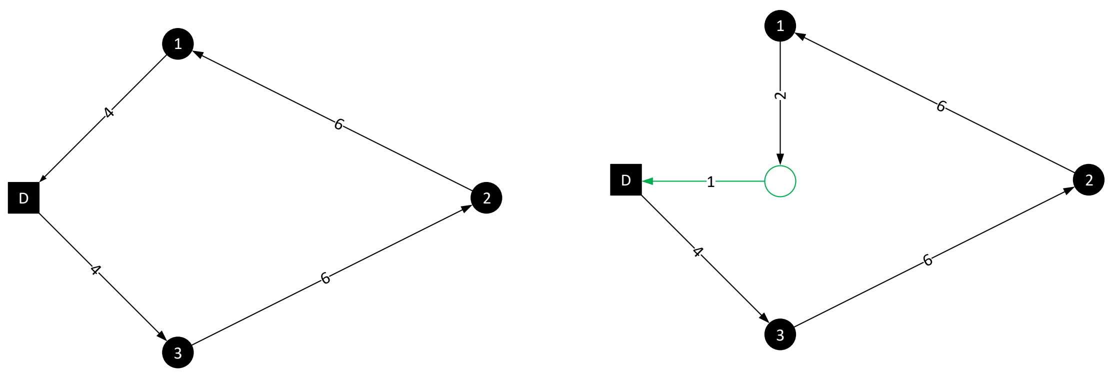
(b) Dynamic Re-optimized Tour

Figure 6.5: VRP Tours with Traffic Management Strategy Change at t=10

lution, we present a situation of the exemplary problem from Section 6.2. In this instance, the traffic strategy one, as seen in 6.3a, is active at the beginning and at time point t = 10, the traffic management changes the traffic strategy to strategy two, which is illustrated in 6.3b. The optimal solution for the static problem with an a-priori approach with strategy one is the sequence $\Theta_{\text{a-priori}}(D-3-2-1-D)$. The tour could also be planned in the reversed order with same result, but for this example we consider this case. An estimated cost for a delivery cost is the predicted on the information that is available in the decision point at the beginning of the tour. The a-priori tour has an estimated tour duration of $\overline{\tau_{\text{estimate}}}(\Theta_{\text{a-priori}}) = 20$. However, after t = 10, the matrix changes to traffic strategy two, which is only revealed at that moment and only if the CLSP has a cooperation with the traffic management. After the a-priori tour is completed, the tour duration would therefore result in $\overline{\tau}(\Theta_{\text{a-priori}}) = 24$ as seen in Figure 6.5a, which would be significantly longer than the estimated duration of the planning process at the beginning of delivery. A re-optimization approach with a traffic management cooperation and decision points at each stop (e.g. depot and at each customer) would obtain a VRP solution with the same sequence as seen in Figure 6.5b. In this case, the re-optimization approach decides about the next customer, which also implies the fastest path to the next customer. In the beginning at the depot and later at customer three, the re-optimizing approach follows the route of the a-priori solution (D-3-2). When the vehicle is at customer two at t = 10 the traffic strategy changes. The new solution now suggests the same next customer (3), but in contrast to the a-priori solution, the route uses the intersection from the city transport network. At the next decision point at customer one, the re-optimization is carried out again and induces the inner-laying path over the intersection back to depot. A re-optimization approach would then have a tour duration of $\overline{\tau}(\Theta_{\text{re-optimization}}) = 15$, which is significantly shorter then the a-priori solution.

6.4 Anticipation of Information

In decision making, decisions are usually evaluated after the decision is taken and an external stochastic effect influenced the outcome. The idea of anticipation is to use a predictive model to simulate realistic decision outcomes before actually taking the decision for the decision making process (Rosen 2012). The predicted object is the stochastic external effect. Knowing the outcome of future stochastic effects in advance would in theory improve decision making quality significantly. In reality, this is of course impossible. Therefore, prediction has to be used. Predicting the exact outcome of a future stochastic effect, is called perfect anticipation (Ulmer 2017). This can rarely be achieved. In practice, predictive models are usually accurate to a certain degree, however, there is always the risk that the prediction is wrong. Anticipation can be used either for static a-priori approaches or for dynamic re-optimization approaches and can be realized through various methods in vehicle routing. For easier explanation, we use city network to show the different resulting tours. The decisions, however, were derived from a VRP network.



(a) Dynamic Re-optimized Tour

(b) Dynamic Re-optimized Tour with Anticipation

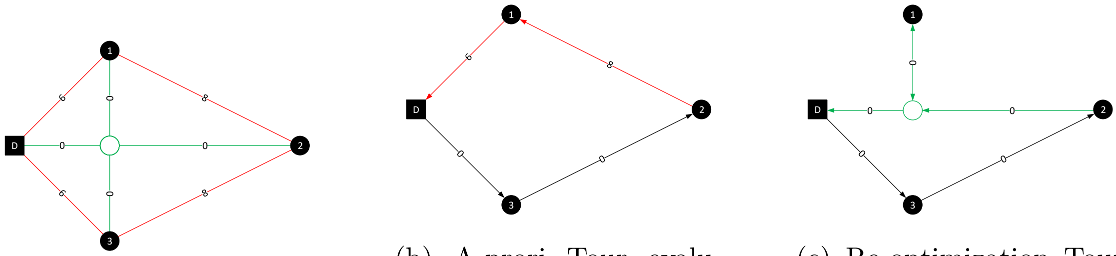
Figure 6.6: Tours with Traffic Management Strategy Change at t=18 in the city network

To show the benefit of a anticipation, Figure 6.6 shows an exemplary planning situation with the two different traffic management strategies from Section 6.2. In this example, the traffic management changes the traffic strategy at t = 18. Figure 6.6a shows the tour (D-3-2-1-D) of a dynamic re-optimization approach. At the decision point at customer one when t = 16, strategy one is active and the re-optimization approach decides to return to the depot via the outside edge with an estimated tour duration of $\overline{\tau}(\Theta_{\text{re-optimization}}) = 20$. In this sample case, we assume that the travel time of an edge that is active at the beginning of the edge traverse is valid for the complete traverse. Figure 6.6b shows the result of a dynamic re-optimization approach with anticipation. For this example, we assume perfect anticipation. In t = 16, the vehicle is at customer one and the anticipation predicts the matrix change at t = 18 correctly. Consequently, the fastest path back to the depot is via the intersection in middle of transport geometry. The tour duration for this scenario would then result in $\overline{\tau}(\Theta_{\text{anticipation}}) = 19$, which results in a small improvement over the re-optimization tour. If a decision at t = 16 was based only on current information, this route from customer three to the depot would not have been chosen as the cost estimation was higher then the direct outside edge (Cost of five via the intersection as to cost of four on the direct connection). Therefore, it is possible with good anticipation methods to improve decision making for vehicle routing problems.

6.5 Reduction of Traffic or Emissions at Hot-Spots

The traffic management is interested in reducing the number of vehicles on the road and the related air pollution. This is especially true for hot-spot areas, where the environmental pollution is high. From a cooperation, the traffic management would expect a reduction of the problem in the hot-spot area. To measure if a CLSP can improve the situation with traffic management information adapted delivery tours, we introduce the performance indicator $\overline{\tau_{\text{TMS}}}(\Theta)$. The hot-spot time $\overline{\tau_{\text{TMS}}}(\Theta)$ indicates the duration a delivery vehicle spends on transport geometry edges that are associated with emission hot-spot areas, where countermeasure against further pollution are active. As only certain edges are associated with hot-spot time we use the original city network to analyze the benefit for traffic management.

Let us assume that when strategy one is active, the pollution is low and no hot-spot time occurs. Therefore, no edges are associated with a hot-spot time. Strategy two from 6.3b is used by the traffic management, when the outside ring of the transport geometry has a high pollution level and is associated with higher travel times



(a) $\overline{\tau_{\text{TMS}}}$ of Strategy Two

(b) A-prori Tour evaluated with the hot-spot time $\overline{\tau_{\text{TMS}}}$

(c) Re-optimization Tour evaluated with the hot-spot time $\overline{\tau_{\text{TMS}}}$

Figure 6.7: Tours with Traffic Management Strategy Change at t=10

to reduce traffic loads through traffic management actions on the outside edges. The outside edges are therefore marked as hot-spot time edges as seen in 6.7a. In this example, the inner-edges are not a pollution hot-spot and therefore have a hot-spot time of 0. We draw on the example from Section 6.3 with a strategy change at t=10 and the two routing approaches (A-priori & re-optimization). Each of these tours is evaluated with the hot-spot times as seen in 6.7b and 6.7c. It can be discovered that the re-optimization approach automatically avoids the edges which have a negative impact as they are associated with higher travel times. The hot-spot time is $\overline{\tau_{\text{TMS}}}(\Theta_{\text{re-optimization}}) = 0$. The a-priori approach can not react and therefore has not only a longer duration, but also a higher hot-spot time of $\overline{\tau_{\text{TMS}}}(\Theta_{\text{a-priori}}) = 14$. Of course the presented example is simple and the traffic management strategies in the later presented case study are far less straightforward. Furthermore, the transport geometry of the case study does not always offer these clearly differentiating path alternatives between any two customers. However, the case study includes more customers, wherefore the importance of the customer sequence will be significantly higher.

Chapter 7

Case Study

The case study takes place in the city of Braunschweig, where an environmental sensitive traffic management system has been planned and as of spring 2017 has undergone testing. In this case study, we are recreating the traffic management system in a simulation to analyze the relationship to city logistics. In this chapter, the case study for the computational experiments is described. Therefore, we first describe the city transport network and then explain the environmental sensitive traffic management system of Braunschweig in Germany. Further on, we show an air pollution data set, which is used to control the emission trajectories in the simulation.

7.1 City Transport Geometry

The city of Braunschweig has around 240,000 residents and is a very typical medium sized European city with its circle-shaped transport geometry layout. A highway circuits most of the city by about 75 % of city except east of the city. The inner city's transport geometry is structured around two inner-city street rings. The smaller city street ring is shaped quadratically with diameter of 600-700 meters and is directly formed around the city center. The second ring encircles in essence the smaller ring with a diameter of 2.5 - 3 kilometers. Furthermore, the highway works in essence as an extra city ring. From the inner-city ring, streets reach outwards away from the city center and thereby connect the ring streets. However, it is not everywhere possible to connect the rings street as a river flows around the inner-city and limits transportation network.

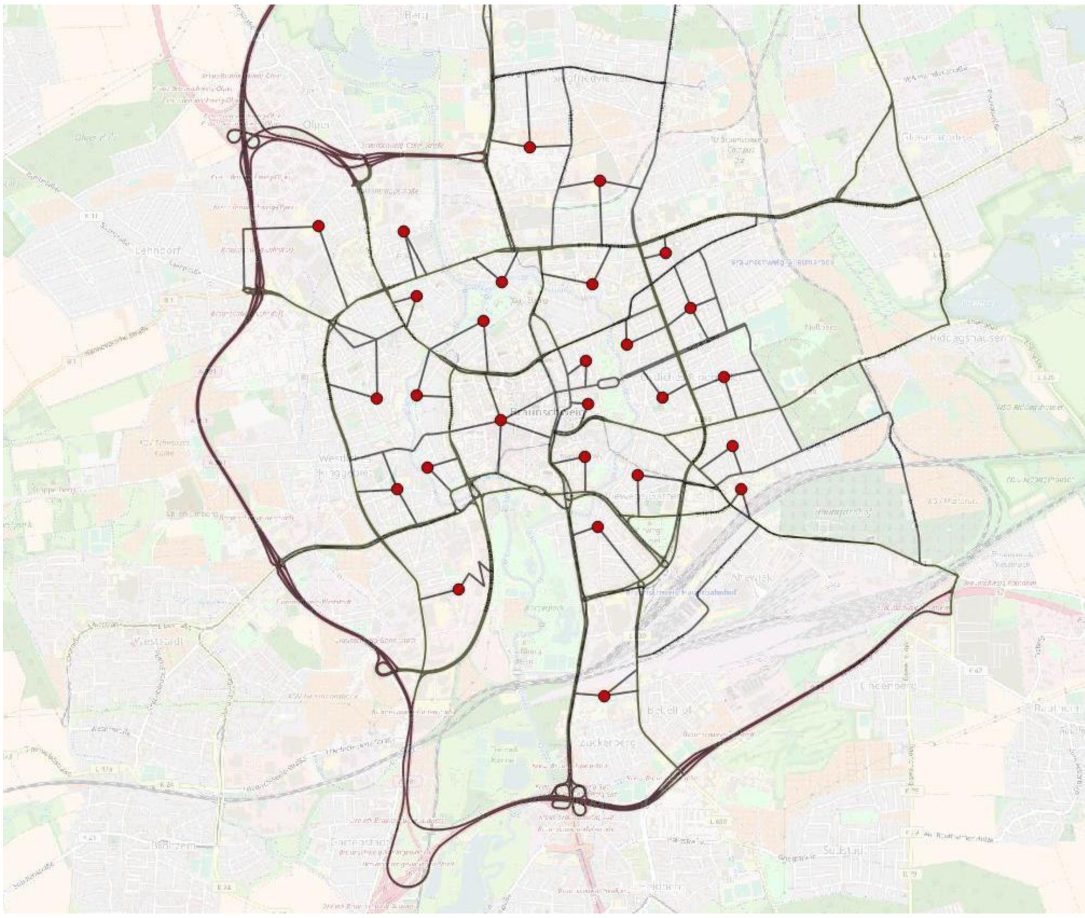


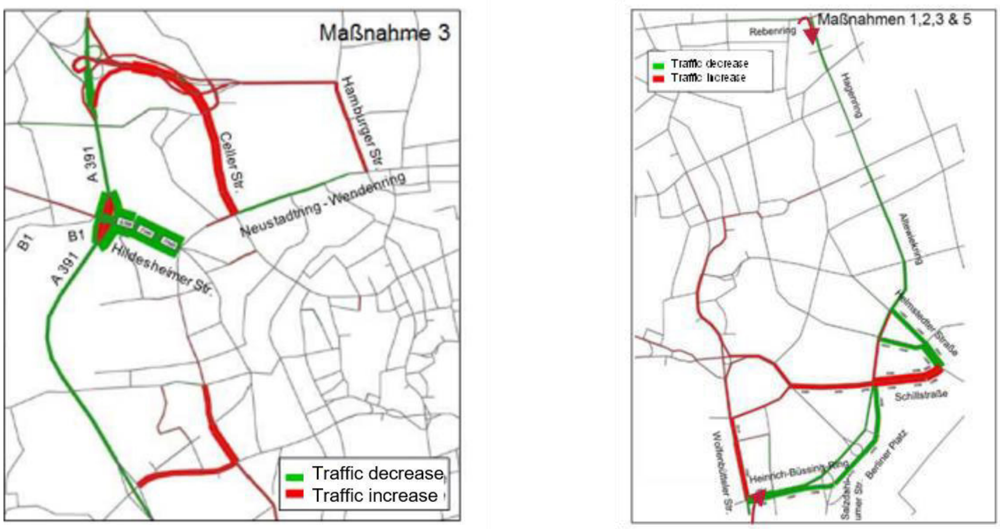
Figure 7.1: Map of Braunschweig (OpenStreetMap Contribution 2017)

The street network for the case study simulation uses data from OpenStreetMap.org. Therefore, Braunschweig regional road network data was selected and processed to it state as seen in figure 7.1. The network graph of the transport geometry has 880 edges and 567 nodes. In the figure, the roads are represented in black color and a real-world satellite picture layer fills the background. The 27 customers are symbolized by red dots. The customers and their locations are designed after actual residential districts of Braunschweig. The travel speed on the transport geometry on an edge that is currently not affected by a traffic strategy is set to 25 km/h. This speed value for the case study lies in between the average of 19 to 35 km/h for major EU cities (Statista 2015).

7.2 Environmental Sensitive Traffic Management System of Braunschweig, Germany

Figure 7.2: Hot-Spots and Critical Pollution Areas in the City of Braunschweig (Bellis et al. 2010)

The case study is modeled after the dynamic environmental sensitive traffic management system in Braunschweig, Germany. For the modeling, two extensive research reports of the working group for the traffic management project were used (Bellis et al. 2010, 2012). The Figure 7.2 shows hot-spots in Braunschweig, where the air pollution counter measure were investigated. The city has five hot-spots, where the air polution exceeds the EU regulation regularly. Colored rectangular boxes indicate critical air pollution areas. The red boxes symbolize critical areas where the yearly NO_2 average is over 40 $\mu g/m^3$. Yellow box indicate areas, which are barely under the EU emission limit. In these areas, the NO_2 air pollution is between 36 to 40 $\mu g/m^3$. Areas, which are not marked by a colored box have an uncritical air pollution value. The air pollution evaluation was been made, before the emission-sensitive traffic management system was installed. Internal simulation tests by the associated research group showed that the hot-spots two and five are dependent on the other hot-Spots. Therefore, these hot-spot were not considered for air pollution countermeasure through the dynamic traffic strategies (Bellis et al. 2010, 2012). Hot-spot one is in the northwest of city at a place where a lot traffic is entering and leaving the city. Hot-spots two and five are on the second city ring. Hot-spot 3 is north of the city center on the inner-city ring and part of a major east-west connection inside the city. Hot-spot four is by far the biggest air pollution area in the city of Braunschweig as the east part of the city is not encircled by a highway. Here, the entire east side of the second ring has either exceeded or is close to exceeding the EU limits.



(a) Effect of Traffic Management actions on Hot-Spot 1

(b) Effect of Traffic Management actions on Hot-Spot 4

Figure 7.3: Hot-Spots in city of Braunschweig (Bellis et al. 2012)

The Figures 7.3 and 7.4 show for the hot-spots one, three and four how the traffic load for individual edges in their respective got-spot area would change if the traffic strategy for less air pollution was activated. Keep in mind an activation of a traffic strategy among others changes traffic light programs and variable message signs on the highway. A red coloration of an edge implies a increase in traffic load, which in networks leads to an increase of the travel time to traverse this edge as this moves the street close to its vehicle capacities limit. Green colored edges are affected by a lighter traffic burden, which results in a decrease in travel time. The level of travel time change through a traffic strategy is highly dependent on the amount of the current traffic load. This effect is naturally higher if there are already more vehicles on the road, i.e. during commuting peak times. Therefore in the case study, we assume different levels of influence of traffic strategies, which is detailed in Chapter 10.

Figure 7.4: Effect of Traffic Management Actions on Hot-Spot 3 (Bellis et al. 2012)

For hot-spot, one the results of a traffic strategy against air pollution are seen in Figure 7.3a. The strategy prolongs the red light time for traffic participants, which are exiting the highway at the Hildesheimerstrasse. Furthermore, variable message signs warn of these traffic measures already on the highway. This results in reduced traffic load around the actual hot-spot area, where adjacent traffic signals are synchronized as well. As a result, other highway exit options are more crowded by vehicles and a higher traffic load occurs. The anti air pollution traffic strategy implies a series of traffic measure to reduce further emissions. Hot spot four's air pollution traffic strategy limits the traffic flow into the associated ring street area from the north, south-west and south through long red intervals as symbolized by red arrows in Figure 7.3b. Inside the hot spot area, the traffic measures synchronize the intersections to reduce the stop-and-go behavior of the traffic participants which also results in an increased travel speed and less emission production. Figure 7.4 shows the drastic traffic strategy measure for hot-spot three, which closes a significant east-west street segment to traffic. Therefore, many traffic participants have to take longer detours around the hot-spot area. This results in a significant limitation of the east-west traffic and results in a reduced traffic load for these directions. However, the detour path to the north is higher frequented.

7.3 Environmental Data Set

It is important for the case study to have accurate NO_2 air pollution trajectories for the model as they govern the activation of the hot-spot traffic strategies and therefore the travel times between the customers of the CLSP. In the simulation, a dataset of the "Niedersächsische Ministerium für Umwelt, Energie und Klimaschutz" (Environmental Department of Lower Saxony, Germany) is used for this. For each of the three hot-spots, an individual monitoring point collected air pollution values from a three month period in the beginning of 2016 in Braunschweig, Osnabrück and Hannover. The later two cities are in the vicinity of Braunschweig and the use of their air pollution data from there should allow to model the non spreading and very local behavior of NO_2. The data from Osnabrück and Hannover shows a strong Pearson coefficient correlation of 0.75 and 0.65 to the data set of Braunschweig, which shows that they have a similar behavior as they are affected by similar weather conditions. At the same time, they are different enough to represent NO_2 emissions for different simulated hot-spots in the case study.

The course of NO_2 air pollution trajectory is stochastic and does not follow a specific pattern. It is especially unpredictable if the NO_2 is over the traffic management action threshold value ψ of 60 $\mu g/m^3$. Figure 7.5 shows three consecutive Wednesdays from the Braunschweig air pollution monitoring station from the August of 2015. The graph shows the daytime in hours between 06.00 and 22:00 on the x-axis and the air pollution value in $\mu g/m^3$ on the y-axis. Furthermore, the graph contains four different data trajectories: The data line of the three consecu-

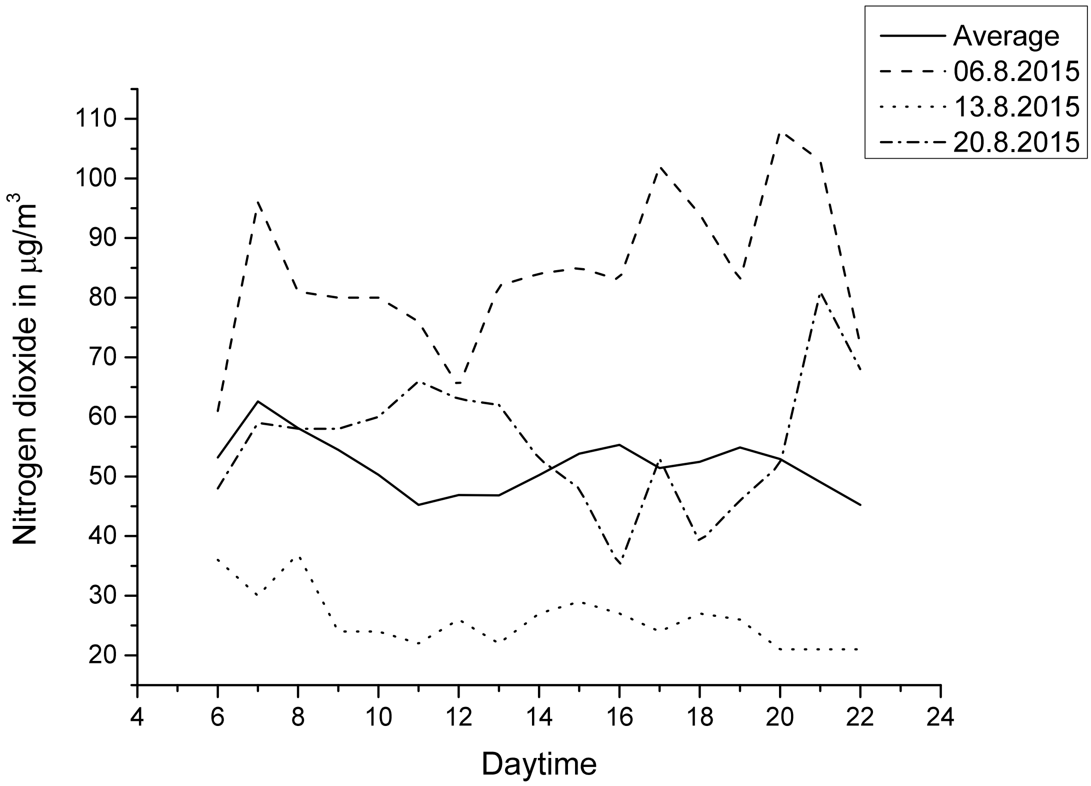


Figure 7.5: Examplary NO_2 Trajectories over Daytime (adapted from Köster et al. (2017b))

tive Wednesday, where the first Wednesday on 6^{th} of august was randomly chosen, and the average air pollution per hours from the complete dataset. In most of the graphs, a morning peak can be discovered between six and eight a clock. Then, all graph lines drop around midday except the data from the 06.08.2015. For the evening it is hard to differentiate, but a small trend towards a rise of air pollution between 14 and 20 a clock can be seen. Therefore, a small correlation between the air pollution and commuting traffic in general can be discovered. However, when evaluating with respect to the traffic strategy air pollution threshold value of 60 $\mu g/m^3$, it is hard to derive at what times the air pollution is above the threshold. We can discover major differences and a high unpredictability if an anti air pollution traffic strategy is active or not. For example on the 6^{th} of August the NO_2 trajectories are above the action threshold for the complete day. However, one week later, the air pollution reaches only air pollution values of 25 $\mu g/m^3$, which would not result in an activation of a traffic strategy. The next week on the 20^{th} of august, the air pollution is above the threshold level from 10 a clock to 14 a clock, which is in contrast to the graph of the average values. Therefore, we believe that the NO_2 trajectories are a stochastic process despite an influence of commuting traffic and that it is especially unpredictable if the air pollution is above the traffic strategy threshold level at any given point of the day.

Chapter 8

Modeling of the Case Study

For the simulation approach in thesis, a two-layered model architecture is used in which the two models are interacting. It can be differentiated between the traffic management system model, which is responsible for the traffic management impacts travel times, and the VRP model, which is responsible for the simulation of logistics activities. The traffic management system's actions impacted individual street links, but the VRP models use aggregated customer-to-customer or customer-to-depot edges. Therefore, each model needs a different network geometry. Figure 8.1 shows the two-layered architecture of the simulation. The traffic management system model calculates the travel times data according to its data input and aggregates them to VRP model specifics, which is defined as the TMS model output. The output is send to the VRP model at each travel time matrix change. If a vehicle in the VRP model is traveling between two nodes when the travel time matrix changes, it's position is send to the traffic management system model as Feedback. There, the remaining travel time to its destination is updated according to the current position and the new impacted on link travel times and send back to the VRP model.

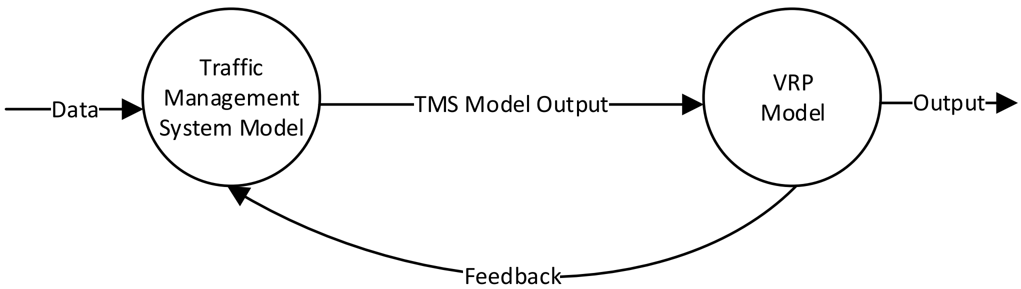


Figure 8.1: Layered Simulation Model

8.1 Modeling of the Traffic Management System

In the following, we describe how the stochastic travel times caused by emission-sensitive traffic management decisions are modeled in the simulation.

8.1.1 Stochastic Travel Times Caused by the Traffic Management Impact

The network $\mathcal{G}$ contains nodes J and edges E. Edges can either be directed edges when the edge represent a one way streets or undirected in case of 2-way streets. Each edge e has an individual length $d(e)$, from which a travel distance matrix $\mathcal{M}^d$ can be calculated with the well known Dijkstra's algorithm (Dijkstra 1959). In the transport geometry, a set of emission hot-spot stations $\mathfrak{S}$ exists. Each hot-spot station σ_m constantly monitors the emission's behavior $N(\sigma)$ in its vicinity. In the model the stochastic emission distribution is represented through a data set with hourly data points $\mathcal{F}$ and therefore changes during the day. If the threshold level Ψ is exceeded by the emission level $N(\sigma_m)$ at station m, the status $r(\sigma_m)$ of this station is set to "active". This results in an adjustment of the traffic strategy and therefore the traffic measures are changed to avoid further traffic air pollution in the hot-spot area. Hereby, the traffic strategy change affects the traffic and the travel time $\tau_{e_z}^{r(\sigma_m)}$ of an edge e_z from the set of edges z of the transport geometry and therefore also the travel time matrix $\mathcal{M}^\tau$. A strategy nevertheless does not influence all edges. The status of a hot-spot station is reverted to "inactive" if the air pollution is reduced to under the threshold value Ψ. The traffic management also calculates a reliable short term emission forecast ϕ, which is in essence a short term travel time matrix forecast. When considering all hot-spots of the model, the statuses of the hot-spots can be realized as an m-dimensional binary vector N. Each vector combination realizes its own individual travel time matrix. With m hot-spots and with two statuses per hot-spot, the number of possible matrices $\mathcal{M}$ is 2^m matrices.

8.1.2 Computation of the Travel Time of an Edge Affected by a Matrix Change

The network is defined as a First-in-first-out (FIFO) network. That means the vehicle that enters an edge first, leaves it first as well. Consequently, waiting is never beneficial. Whenever a matrix change is enforced and the travel time of an

Table 8.1: Modeling of the Traffic Management and Stochastic Travel Times

Planning Element	Mathematical Formulation
Network Graph	$\mathcal{G}$
Travel Distance of Edge e	$d(e)$
Hot Spot Stations	$\mathfrak{S} = \{\sigma_1, \ldots, \sigma_M\}$
Emission level of Hot-spot of σ_m	$N(\sigma_m)$
Status of Hot-Spot Stations	$r(\sigma_m)$
Emission level vector	N
Traffic Management Threshold Level	Ψ
Stochastic Emission Distribution	F
Traffic Management Emission Forecast	Φ
Travel Time of Edge e_z	$\tau_{e_z}^{r(\sigma)}$
Travel Time Matrix	$\mathcal{M}^{\tau}$
Time when Vehicle is at Node a	t_a
Time when Vehicle is at Node b	t_b
Travel Distance of edge between a and b	$d_a b$
Distance Traveled of an Edge at Point t	d_{ab}^t
Previous Travel Time of Edge e_z	τ_e^{previous}
Current Travel Time of Edge e_z	τ_e^{current}
Travel Time of Edge e_z at Point t	$\tau_{e_z}^t$

edge is recalculated. This is critical for vehicles, who are traveling on the edge at the moment of the travel time change, as this could violate the FIFO constraint. For adjusting travel times for a vehicle, we use the approach from Ichoua et al. (2003), which was further advanced by Eglese et al. (2006). The authors recalculate the arrival time of a vehicle at a node if the travel time of the edge z changes while the vehicle is traversing it.

$$t_b = t_a + \frac{d_{ab}^t}{d_{ab}} \tau_{e_z}^{\text{previous}} + (1 - \frac{d_{ab}^t}{d_{ab}}) \tau_{e_z}^{\text{current}} \tag{8.1}$$

If a vehicle is on an edge e_z with a start node a and end node b during a matrix change, the new arrival time t_b at the edge's end node is determined by the function 8.1. In this case, t_a marks the point in time when a vehicle starts traversing the edge from the start node. At the point in time t when the travel time matrix changes to the new current travel time matrix, the distance d_{ab}^t that the vehicle has traveled on the edge so far is measured. This distance is put into relation with the total distance of the edge d_{ab} and multiplied with the previous travel time for this edge τ_e^{previous}. The remaining part of the edge $(1 - \frac{d_{ab}^t}{d_{ab}})$ is then multiplied with the current edge travel time τ_e^{current} and added to the other part of the equation.

$$\tau_{e_z}^t = \frac{d_{ab}^t}{d_{ab}} \tau_{e_z}^{\text{previous}} + (1 - \frac{d_{ab}^t}{d_{ab}}) \tau_{e_z}^{\text{current}} \tag{8.2}$$

The equation 8.1 is reformulated in equation 8.2 to calculate the travel time of an edge, which is affected by a matrix change. As an explanation, we provide an example. An edge has a distance of $d_{ab} = 4$ km and a travel time of $\tau_e^{\text{previous}} = 4$ minutes with the traffic strategy that is active previous to the change. At the time t of the change, the vehicle has traveled $d_{ab}^t = 2$ km. The new travel time with the now current τ_e^{current} is 2 minutes. Now the travel time for the edge at time t is therefore: $\tau_{e_z}^t = \frac{2km}{4km}$ 4 minutes + $(1 - \frac{2km}{4km})$ 2 minutes = 3 minutes.

8.1.3 Time-Dependent Shortest Path Calculation

In graphs where the travel times of the edges are not constant, classical static shortest path calculation, which can be for example be calculated with Dijkstra's algorithm, are used as a basis for decision making. The outcome of such a static shortest path problem is not the correct representation of the travel time from a start point to any other location in a graph as the variability of the travel time is not considered. If the emission forecast and therefore the next travel time matrix with the exact transition time between two travel time matrices is known, it is possible to calculate a time-dependent shortest path matrix. In comparison, to a static shortest path calculation the structure of the underlaying graph is different. In a static case, a graph for a shortest path problem will be solved with the travel time τ as edge weight for example. In a time-dependent case, the travel time is now dependent on t and is defined as $\tau(t)$. For a city logistics vehicle routing problem with time-dependent travel times, a time-dependent shortest path problem was solved by Ehmke (2012), who used a series of hour time bins.

The time-dependent Dijkstra' algorithm is a modification of the standard Dijkstra's algorithm. Algorithm 1 shows the respective pseudo code which considers the travel time τ as edge weights. The algorithm introduces two labeled node lists: The preliminary labeled list R and the as final labeled list Q. In the beginning, the start node is added to the preliminary list R and the list Q, which represents completely processed nodes, is empty. The travel time $\tau(s)$ to the start node is set to 0 and the distance from the start node to all the other nodes is set to infinity. Now as long as R is not empty, the node i with smallest value of $\tau(j)$ is chosen. The node is than removed from R and added to Q. In contrast to the standard Dijkstra's algorithm,

Algorithm 1: Time-dependent Dijkstra's Algorithm

Input : Time-dependent graph with edge weights of $\tau(t)$, start node s
Output : Time-dependent fastest path from start node s to all other nodes in the network

Initialization
$\tau(s) = 0$; p(s) := 0; R:=s; Q := $\emptyset$;
$\tau(j) := \infty$ for $j := 1, ..., J; j \neq s$;
Processing
while $R \neq$ *empty* **do**
  Choose one $i \in R$ with $\tau(i) = \min\{\tau(p) : p \in R\}$;
  Set $R := R \backslash \{i\}$ and $Q := Q \cup \{i\}$;
  for *all successors* $y \in Y(i)$ *with* $y \in Y(i) \backslash Q$ **do**
    t :=$\tau(i)$;
    Check whether $\tau(y) > \tau(i) + \tau_{iy}$(t);
    if $\tau(y) > \tau(i) + \tau_{iy}(t)$ **then**
      Set: $\tau(y) := \tau(i) + \tau_{iy}$(t);
      p(y) :=i;
      if $y \subsetneq R$ **then**
        R = R $\cup$ y;
      end
    end
  end
end
Terminate if R = $\emptyset$;

the travel time $\tau_{iy}(t)$ from node i to a successor node y from i's set of succor nodes Y is dependent on the time point t when edge weight is used in this shortest path calculation. The algorithm checks if the combined travel time of time to i and then to the successor node y is shorter then the previous known shortest travel time $\tau(y)$. If it is shorter, $\tau(y)$ is set to $\tau(i) + \tau_{iy}$(t) and i is added to R if it is not already in that list.

8.2 VRP Model

To investigate the problem of the relationship between environmental sensitive traffic management impact and city logistics activities, we use two different vehicle routing models and vary the travel time matrices to simulate the different cooperation levels. In this chapter, we define the two different dynamic vehicle routing problems with stochastic changes of travel time matrices (DVRPMC). Therefore, we give a detailed problem statement for the VRP I in Section 8.2.1 and only describe the deviations that were made for the VRP II in Section 8.3. Finally, we use a Markov decision process to model the decision process for each VRP (Puterman 2014).

8.2.1 Vehicle Routing Problem I

In the vehicle routing problem one (VRPI), a fleet of o freight vehicles $\mathcal{V} = \{v_1, \ldots, v_o\}$ carries goods to a set of customers $\mathcal{C} = \{c_1, \ldots, c_n\}$. The delivery fleet starts and end their tours at a depot D. The goods are heterogeneous, which implies that a customer needs his specific freight goods. In our case, the freight vehicles' capacities are unlimited. The problem is formulated as a complete graph $\mathcal{G}_{\text{VRP}} = (\mathcal{C}, E)$ and is derived from the road network $\mathcal{G}$ of the case study. It consists of nodes, which are the customers $\mathcal{C}$ and the depot D. The edges E_{VRP} connect the nodes of the VRP and have a travel time and a distance. The customers are known in advance and are located on the transport network graph. Furthermore, each customer n has a service time of t_n^{service}.

Table 8.2: Modeling of the Vehicle Routing Problem 1

Planning Element	Mathematical Formulation
Point of Time	$t \in T = [0, ..., t_{\max}]$
Network Graph	$\mathcal{G}_{\text{VRP}}$
Travel Distance Matrix	$\mathcal{M}^d$
Travel Distance Time	$\mathcal{M}^\tau$
Depot	$\mathrm{D} \in \mathcal{G}$
Customers	$\mathcal{C} = \{c_1, ..., c_n\} \in \mathcal{G}$
Status of C_n	$\mathrm{r}(C_n)$
Service Time of C_n	t_n^{service}
Vehicles	$\mathcal{V} = \{v_1, ..., v_i\}$
Assigned Customers to Vehicle V_i	$V_i(C_1^i, .., C_{\max}^i)$

In the beginning of the problem, the dispatcher assigns customers to vehicles. Each vehicle therefore has a delivery list $V_i(c_0^i, .., c_{\max}^i)$. The goods are then loaded to a vehicle and the assignment is permanent. The dispatcher then routes each vehicle to all its assigned customers. The dispatcher can decide about the sequence in which the customers receive their deliveries. Keep in mind, with this decision and according to the information state of the dispatcher, this results also in certain paths between the customers in the more detailed traffic management simulation with the network graph $\mathcal{G}$. During the day, the travel time matrix $\mathcal{M}^\tau$ can change, which instantly affects the travel times between all customers and the depot for all vehicles. The travel time matrix $\mathcal{M}^\tau$ is stochastic, discussed in detail in Section 8.1.1 and updated accordingly whenever it changes. At an update and when a vehicle is currently traveling to a customer, it's remaining travel time is then adjusted according to the impact of the traffic management system on that edge.

Vehicles can only be rerouted at customer locations or in the beginning of the delivery problem at the depot. Therefore, modifications the customer delivery sequence are not allowed when the vehicle is traveling. When a vehicles arrives at a customer location its position l_i is updated accordingly. A customer receives his delivery when the vehicle, which has his goods loaded, is at his location. This customer is then neglected in future routing decisions. Afterwards, the dispatcher can adjust the sequence of the remaining deliveries and the related paths of this vehicle. The objective is to minimize the travel times for all vehicles of the delivery fleet.

8.2.2 Markov Decision Process for VRP I

The presented DVRPMC is a vehicle routing problem with stochastic and dynamic elements and can be modeled as a Markov decision process (Ulmer et al. 2016). At a decision point, a situation in the model is described as a state. Before the delivery tours of the fleet can start, the initial decision about the distribution of the customers' goods to the delivery vehicles has to be made based on the initial state S_0, which consists of the entire set of customers $\mathcal{C}$ and the current travel time matrix M_0 of the overall set of travel time matrices $\mathcal{M}$. This is a permanent decision and decides, which vehicle delivers goods to which customer. Afterwards, the decisions processes for the vehicles can be considered independently.

Table 8.3: Entities in the MDP for VRP I

Planning Element	Mathematical Formulation
Decision Point	k
State	S_k
Current planned tour	θ_k
Customer Sequencing Update	θ_k^x

Each tour of each vehicle begins and ends at the depot D. The decision points k occur each time a vehicle has finished a delivery to a customer. A state $S_k = (t_k, l_k, \mathcal{C}_k, \theta_k, \mathcal{M}_k^\tau, N_k, \phi_k)$ of the decision point k is composed of the point in time t_k, the vehicle's location l_k at the current customer, the remaining customers' delivery orders $C_k \subseteq \mathcal{C}$, the currently planned tour θ_k, the vector N_k, which represents the current emission levels of every station $\sigma \in \mathfrak{S}$, the active travel time matrix $\mathcal{M}_k^\tau \in \mathcal{M}^\tau$ and the emission forecast ϕ_k at the current decision point. As the goal in our experiments is to examine the benefits of a cooperation between traffic management and logistic service provider, the state space's information level is limited in some experiment variants. A decision $x_k \in \mathcal{X}(S_k)$ is made on the routing update θ_k^x. This includes the next customer C_{next} to visit. The transition to the next State S_{k+1} is split into a deterministic element from the decision and a stochastic element from a potential change of the travel matrix. Therefore, the stochasticity of the transition influences the time t_{k+1} of the next decision point when the vehicle arrives at the location l_{k+1} of customer C_{next}. Furthermore, it realizes the change in the emission levels of vector N_k and the therefore realized matrix $\mathcal{M}_k^\tau$ to $\mathcal{M}_{k+1}^\tau$ and N_{k+1}. The new state is then realized as $S_{k+1} = (t_{k+1}, l_{k+1}, \mathcal{C}_{k+1}, \theta_{k+1}, \mathcal{M}_{k+1}, N_{k+1}, \phi_{k+1})$.

A decision's outcome is the choice of the next customer and the associated expected travel time $R(S_k, x)$ to the next customer C_{next}. Notably, this is a random variable because of the possible stochastic matrix changes. The stochastic transition ω_k therefore affects the vehicle, which is traveling on an edge to the next customer through the travel time matrix change. The termination state $S_K = (t_K, D, \emptyset, \theta_K, \mathcal{M}_K, N_K, \phi_K)$ is reached when all customers are served and the vehicle is back at the depot $l_K = D$.

A decision policy $\pi \in \Pi$ is a solution for the MDP. A policy $\pi = (X_0^\pi, \ldots, X_{K-1}^\pi)$ represents a sequence of decisions X_k^π at the decision points. A decision rule determines the decision $x = X_k^\pi(S_k)$ for a state S_k. The objective function for the DVRPMC is to minimize the expected overall travel time with an optimal policy π^* as depicted in Equation 8.3.

$$\pi^* = \underset{\pi \in \Pi}{\arg\min}\, \mathbb{E}\left[\sum_{k=0}^{K} R(S_k, X_k^\pi(S_k))|S_0\right] \tag{8.3}$$

8.3 Modifications for Vehicle Routing Problem II

The vehicle routing problem II (VRP II) is a pick-up problem, where not all customers from the customer set $\mathcal{C}$ are known at the beginning of the day. The customers that are known at the beginning of the day are called early request customers C^{erc} and the customers that request a pick-up service during the day are defined as late request customers C^{late}. These requests are pick-up requests. The ratio between late requests (also dynamic requests) and total requests is defined as Degree of Dynamism (DoD) (Larsen et al. 2002). A DoD of 0.2 symbolizes that 20% of the customer request are known in advance and the remaining 80% are revealed during the day.

Table 8.4: Additional Modeling for the Vehicle Routing Problem II

Planning Element	Mathematical Formulation
Early Request Customers	C^{erc}
Late Request Customers	C^{late}
Request Time of Late Request Customers	$t_{request}(c_b^{late})$
Degree of Dynamism	DoD

In the beginning of this planning problem, the early request customers are assigned to vehicles and the routing with the early requests is realized for each vehicle as in VRPI. During the day, not only does the travel time matrix change, but also the additional late customer requests come in. At decision points, the dispatcher has to assign the requests that appeared between the current and the last decision point permanently to a vehicle of the fleet and then incorporate the requests into the tour plan of a vehicle. As before, the objective is to minimize the travel times of the complete fleet, while all customers must be served. In order to be served, the requests must arrive until 12:00. In our model, a poison distribution decides about the request times $t_{request}(c_b^{late})$ of late request customers.

8.3.1 Markov Decision Process for VRP II

Table 8.5: Additional Entities in the MDP for VRP II

Planning Element	Mathematical Formulation
Request at Decision Point	$r(c_k^{late})$

In differentiation to the VRP I, VRP II also handles stochastic customer requests. Hereby, not all customers are known at beginning of the day and the early request customers are a subset $C^{erc} \subseteq \mathcal{C}$. The remaining customers C^{late} will request a pick-up during the day and are part of the state $S_k = (t_k, l_k, \mathcal{C}_k, \theta_k, M_k, N_k, \phi_k, r(C_k^{late}))$. At each decision point k, it is possible that a number of late customer requests $r(C_k^{late})$ require a service. The exact request times and which customer of the remaining customers are requesting is part of the transition function ω_k. Therefore, at each decision point k, the policy decides first which vehicle serves which new customer request. Then, the routing and path finding decisions from the policy are made as in VRP I.

Chapter 9

Methods

In this chapter, we describe the used methods to solve the model from Chapter 8.2 and explain the used the industrial solver Spider in Section 9.1. Therefore, we first explain the the underlaying conceptual model of Spider in 9.1.1, the associated mathematical formulation is presented in 9.1.2 and in 9.1.3 Spider's algorithm that solves the formulation is presented. In Section 9.2, we present our developed approach Partial Time-dependent Sampling, which improves the routing performance with Spider and introduces anticipation of future travel times into a standard solver. Hereby, we sample possible future air pollution values to predict the traffic management behavior, which in our problem is in essence a prediction of future travel times. Finally, we introduce an adapted nearest insertion method for the distribution of the dynamic customer requests between the vehicles of the delivery fleet in VRP II in Section 9.3.

9.1 Spider

Spider is a commercial routing software and was developed by SINTEF Applied Mathematics in 1995. Since then, Spider was continuously improved through EU research programs (i.e. Greentrip) and industry contracts (i.e. with the Norwegian telecommunication company Telenor Mobil) and is now in use by multiple companies in applications like waste management, mail delivery, and newspaper distribution. The software has been validated to produce good results in empirical tests and also produces so far best known solutions in some variants of Solomon's test instances and their extensions (Hasle and Kloster 2007). Spider can solve static Vehicle Routing Problems. For dynamic decision making, we treat the decision situation of decision point as a static VRP and solve it with Spider. From the Spider solution, we extract the next customer from the customer sequence and use it as the solution from decision point. Then, the simulation handles the transition to the next decision point.

9.1.1 Spider's Conceptual Model

Figure 9.1 shows the conceptual model of Spider, which is a representation of Spider's system and also shows the interaction of its individual components. A problem that can be solved by Spider is defined as a VRP, which consists out of the topology, orders, tasks, tours, objectives and constraints as seen by the arrows in the figure. The topology defines underlaying transport network geometry and can either be an Euclidean plane or a road network. Orders are customer pick-up requests or delivery orders and if they are accepted by dispatcher they become order tasks. If an order task is assigned to a tour, it is defined as a task. The delimiter tasks are the start and end location of the tour. The order tasks and delimiter tasks are assigned to a tour through the solver of the VRP. Therefore, each tour is an ordered sequence of tasks and needs an equipages, which consists out of a vehicle and a driver who can attend the tour. In many classical VRPs, the objective is to minimize the travel distance. Spider offers a wide variety of objectives like minimization of distance, driving cost, travel time, fleet size, emissions or maximization of profit. The constraints limit the resources of the problem. The number of available vehicles and driver or their properties can have significant effect on the solution. Furthermore, common constraints are for example the driver working times, which in some countries are governed by legislation, the vehicles' capacity or customer specific constraints like time windows (Hasle and Kloster 2007).

To investigate the research question of the relationship between dynamic traffic management, i.e. an environmental-sensitive traffic management system, and the derived problem from Section 8.2, we modify the topology, orders and constraints to fit the problem.

9.1.2 Mathematical Formulation of Spider Conceptual Model

The mathematical formulation of our problem is rather simple, which is in contrast to the rather complicated travel time changes in the model. For Spider, we derive deterministic instances of the problem, which are then evaluated with the stochas-

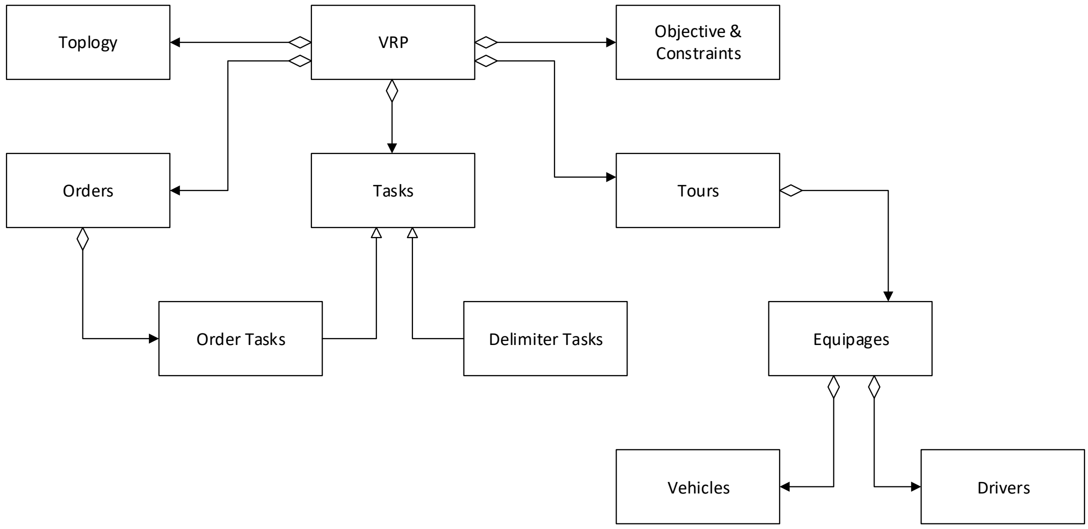


Figure 9.1: Conceptual Model of Spider (adapted from Hasle and Kloster (2007))

tic travel times in a simulation. Therefore, the problem is NP-hard and can be formulated as a mixed integer linear program for Spider (Hasle and Kloster 2007).

$$minimize \sum_{v \in V} \sum_{i,j \in A} \tau_{ij} x_{ij}^{v} \tag{9.1}$$

$$\sum_{v \in V} \sum_{j \in C} x_{ij}^{v} = 1, \forall i \in \mathcal{C} \tag{9.2}$$

$$\sum_{j \in C} x_{Dj}^{v} = 1, \forall v \in \mathcal{V} \tag{9.3}$$

$$\sum_{i \in C} x_{ih}^{v} - \sum_{j \in C} x_{hj}^{v} = 0, \forall h \in \mathcal{C}, \forall v \in \mathcal{V} \tag{9.4}$$

$$\sum_{i \in C} x_{iD}^{v} = 1, \forall v \in \mathcal{V} \tag{9.5}$$

$$x_{ij}^{v} \in 0, 1, \forall (i, j) \in \mathcal{C}, v \in \mathcal{V} \tag{9.6}$$

The objective in (7.1) represents the goal to minimize the sum of travel times of all vehicles over all used edges. The constraint in (7.2) determines that all customers must be served exactly once and (7.3) enables that there is one tour per vehicle. (7.4) forces a vehicle that arrives at a customer not to wait there and to leave the customer location again. The return to the depot by the fleet is ensured by the

Algorithm 2: Pseudo Code of the Savings Algorithm

```
   Input : Customers C, Depot D
1  Construct a list of tours with n commuter tours;
2  Calculate start savings s_ij with (7.7) for joining two tours with i,j=1,...,n and
     i ≠ j ;
3  Sort the saving values according to value;
4  while s_ij > 0 do
5  |   Choose s_ij = max s_ij;
6  |   if if tours i,j can be joined then
7  |   |   Join tours i & j to new tour;
8  |   |   Recalculate savings s_ij with (7.7) for joining two tours with i,j=1,...,n
   |   |     and i ≠ j;
9  |   |   Resort the saving values according to value;
10 |   |   else
11 |   |   |   Go back to step 5 and use next best savings value s_ij
12 |   |   end
13 |   end
14 end
15 Terminate;
```

constraint (7.5). And lastly, (7.6) forces the decision variable x_{ij}^v to be binary.

9.1.3 The Spider Unified Algorithmic Approach

The Spider Unified Algorithmic Approach is used to solve the model from Section 9.1.2. The idea behind the unified algorithm approach is that it can be used for all types of instances that can be derived through the spider conceptual model. As VRP problems are NP-hard, heuristics are used in a two step procedure. First, an initial tour is constructed in the *Construction* phase with a Savings algorithm, which is then iteratively improved with a Local Search approach in the *Iterative Improvement* phase.

Construction

The goal of the construction phase is to create a starting solution for the iterative improvement Local Search steps. A high quality starting solution can improve the speed of the convergence of the solution significantly. Spider offers a wide variety of standard construction heuristics. In this thesis, we used the Savings algorithm from Clarke and Wright (1964) as it produces good initial solutions.

$$s_{ij} = \tau_{D-i-D-j-D} - \tau_{D-i-j-D} \tag{9.7}$$

The Savings procedure is explained in Algorithm 2. The idea is to construct an individual tour for each customer and then successively to join the tours together. In the beginning of the procedure, for each customer an individual tour from the depot and back is constructed as seen on the left side of Figure 9.2. Then, the savings values s_{ij} as shown in Equation (7.7) are calculated for every possible two tours i,j combination. The saving value in our case represents the amount of travel time that would be saved if these two tours would be joined together. In the next step, the savings values are ordered. Then, a repetitive proceedings starts in step six. The highest saving value is selected and the two tours are joined if the new tour is feasible (i.e. no constraints are violated). Then, the savings values are recalculated and reordered. If the new tour does not result in a feasible solution, the algorithm returns to line five and selects the next highest s_{ij}. The repetitive procedure is repeated until no positive s_{ij} exists or only infeasible tour join options exist.

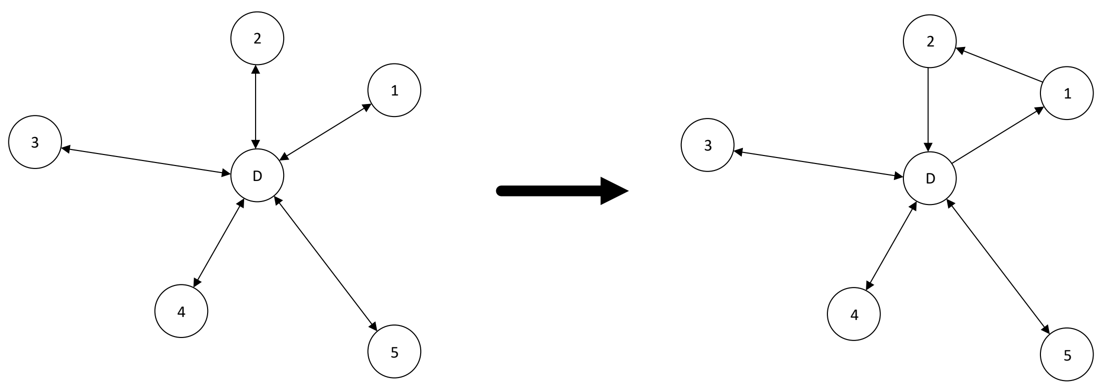


Figure 9.2: A Tour Join Operation of the Savings Algorithm

Figure 9.2 shows two steps in the Savings algorithm procedure. The left side shows the initialization step of the algorithm, where each customer receives an individual delivery tour. Therefore, five tours for five customers exist for the logistics service provider. Now, the savings values are calculated and ordered. In the example, we assume that tours D-1-D and D-2-D have the highest saving value and therefore these two tours are joined as seen on the right side of the figure.

Iterative Improvement

The goal of the iterative improvement phase is to improve the solution quality from the construction phase. The iterative improvement phase is based on the Iterated Local Search, which was developed by Lourenço et al. (2003), and has two sub-phases. First in the *intensification* sub-phase, a local optimum is determined with the Variable Neighborhood Descent procedure from Hansen and Mladenović (1999). Then, the *diversification* sub-phase generates alternative solutions in unexplored and promising solution space areas (Hasle and Kloster 2007). Spider alternates between the two sub-phases until no more improvements can be made or an optimization time-limit is reached.

Algorithm 3 shows how the Variable Neighborhood Descent works. In the beginning, the solution u is imported from the construction phase and $f(u_{best})$ is initialized with a Big M value, which is higher then the solution quality of the starting solution $f(u)$. Now as long as a solution quality $f(u)$ better than the previous best known solution $f(u_{best})$ can be found, a neighborhood search is used. Therefore first, solution u is set to the new u_{best} and its neighborhood $h_{u_{best}}$ is iteratively searched K times, whereas i serves as the count variable. In the iterative search, an operator is used to achieve a new solution u'. If the solution quality $f(u')$ of the new solution is better than f_u, u is updated to the solution of u'. The used operators are a series of

Algorithm 3: Variable Neighborhood Descent (adapted from Hertz and Mittaz (2001))

Import initial solution u from construction phase;
Initialize $f(u_{best}) = BigM$;
while $f(u) < f(u_{best})$ **do**
    Set $u_{best} := u$;
    Set $i := 1$;
    while $i \leq K$ **do**
        Perform operation to move in neighborhood $h_{u_{best}}$;
        Let u' be the resulting solution;
        Set $i = i + 1$;
        if $f(u') < f(u)$ **then**
            Set $u = u'$;
        end
    end
end

well-known intra- and inter-tour variation operators. The intra-tour operators are:

- 2-OPT
- OR-OPT
- 3-OPT

The inter-tour operators are:

- Insert
- Relocate
- Cross
- Exchange
- Sequence Exchange

Such a descent method concludes in the first found local optimum. Therefore, the *diversification* sub phase, that implies a Very Large Neighborhood Search, is used to escape the local optimum. Hereby, a specific number of customers are extracted from the tours and re-inserted using a regret based insertion procedure. The main idea of the regret based insertion procedure is to insert a request in the position of the delivery vehicles' customer sequences where the difference in the value of the objective function is the greatest when comparing the best and second best insertion position.

$$\tau_a^{\text{regret}} = \arg\max_{a \in C^{\text{insert}}} (\Delta f_a^2 - \Delta f_a^1) \tag{9.8}$$

For a set of insertion requests C^{insert}, all regret values must be calculated as seen in 9.8 and then compared so that the request with the highest regret value can be found. Let Δf_a^1 denote the change of the objective function if a request a is inserted in its cheapest position and Δf_a^2 denotes the change of inserting request a in its second cheapest position. The regret value τ_a^{regret}(in our case travel time is the objective function value) is calculated by subtracting Δf_a^1 - Δf_a^2 and symbolizes in essence how much is lost in the objective function if a request can not be inserted at its best position (Pisinger and Ropke 2007). The procedure then iteratively inserts the request with the highest regret value. After each insertion, all τ_a^{regret} values have to be recalculated as one insertion option disappears and two new insertion options were created.

9.2 Partial Time-dependent Sampling

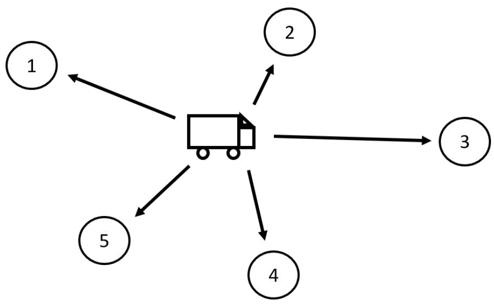


Figure 9.3: Possible Next Customer Stops

The main idea of Partial Time-dependent Sampling (PTDS) is to anticipate critical traffic management actions at the hot-spots and therefore the changes in travel times before they actually happen. Consequently, a delivery vehicle would not drive directly into a for him soon realized unfavorable traffic strategy change, which could reduce the vehicle speed in that area. The Partial Time-dependent Sampling procedure tries to make best use of available information and to allow anticipation through a manipulated travel time matrix that is feeded into a standard static solver. The procedure is seen in Algorithm 4 and consists of three steps. First, at a decision point, the information that the traffic management can provide, which is not only the current traffic strategy, but also a 3 hour long pollution forecast, is used to calculate the travel time from the current location to the next possible customers. Then, a sampling procedure constructs a travel time matrix through simulating the future emission trajectories from historical data. Sampling allows a detailed consideration of possible future events, but requires significant computational effort within the execution phase for the simulation of events. In the final step, the results of the previous two steps are combined into a singe travel time matrix. The PTDS procedure can be done in beginning of the day or at a decision points at customer locations during the delivery process.

Algorithm 4: Determining an anticipating travel time matrix with partial time-dependent sampling

Input : S_k, F_n,F_h, N, E_{history}, n_{max}
Output : An anticipating travel time matrix
Calculate travel times to possible next customers τ_{dj};
Estimate the remaining tour duration t_{est} [hour] with a Nearest Neighbor algorithm;
for $n \leq n_{max}$ **do**
    i = 0;
    while $i < t_{est}$ **do**
        if $i \leq$ *TM emission forecast horizon* F_h **then**
            M_i = forecasted travel time matrix from Traffic Management;
        end
        if $i >$ *TM emission forecast horizon* F_h **then**
            Sample future emission E_i trajectories from last hour emission values $E^N_{\text{i-1}}$ and historical data E^N_{history};
            M_i = travel time matrix with TM effects if $E_i > E^N_{\text{limit}}$;
        end
    end
    $M_n = \sum_{i=0} M_i \ / \ i$;
end
$M_{\text{sampled}} = \sum_{n=0} M_n \ / \ n_{max}$;
Insert τ_{dj} and replace values in M_{sampled};
return M_{sampled}

In the first step, we calculate the travel times from the current location of the vehicle to all other possible destinations as seen in Figure 9.3. A possible arrival at these destination is in the near future and with the information about the current traffic strategy and the assumption, that the forecasted information is correct, the travel time to these destinations is considered deterministic information. The travel time to the next customer is therefore certain and does not need to be sampled as this can be calculated with traffic management information. Therefore in the first step of PTDS at a decision point d at the time t_d, the travel times τ_{dj} from the current location l_d to all other possible destinations j is calculated. This is done by using Dijkstra's algorithm. If, however, a matrix change due traffic management actions is scheduled and known through the available forecast, the path and travel times are calculated with the time-dependent version of Dijkstra's algorithm as presented in Section 7.3.

In the second step of the procedure, we sample future NO_2 emission trajectories E^n for each hot-spot n. From this, we can derive an estimation of future travel time changes with the knowledge about the traffic management action level ψ. At every decision point, we first determine a time horizon limit for the sampling, which in our case is the approximate rest tour duration t_{est} and is calculated with a Nearest Neighbor algorithm (see Rosenkrantz et al. (1974) for details). Figure 9.4 shows an example of the sampling. At decision point at 08:00, the estimated rest tour length is 8 hours and the traffic management forecast is 3 hours until 11 am. Then, for each full hour of the expected remaining tour duration, we build an individual travel time matrix M_i. In the first three hours, the known information of the current traffic strategy and the 3 hour forecast are used to create a travel time matrix for each hour. For the other hours, we sample the emission behavior from historical data and the last known air pollution value. For the historical data, we separated a part of the hourly air pollution for a training set and calculated the average hourly change and the standard deviation. Then, we assume that we have a normal distribution and draw a change value from this distribution for each hot spot and add that to the last known pollution value $E_{\text{i-1}}$ of the hot-spots to receive a fictional possible next pollution value. This continues until the end of the expected tour duration. In the presented Figure 9.4, this is done for five hour points (12:00,13:00,14:00,15:00 and 16:00) With the individual pollution value for each hour, it is possible to derive a travel time matrix for each hour as the traffic changing actions by the traffic management are known. All the travel times are then added and divided by the number of matrices i. This whole process is then repeated N times times to ensure more accurate sampled values. In the end, the travel times matrices from each sample run are added up and averaged.

In the third and final step, the two steps of PTDS are united for a final travel time matrix, which can be used with a solver. Therefore, the travel time values τ_{dj} from the current location to all possible next customers from step one are inserted into the respective position in M_{sampled} of step two.

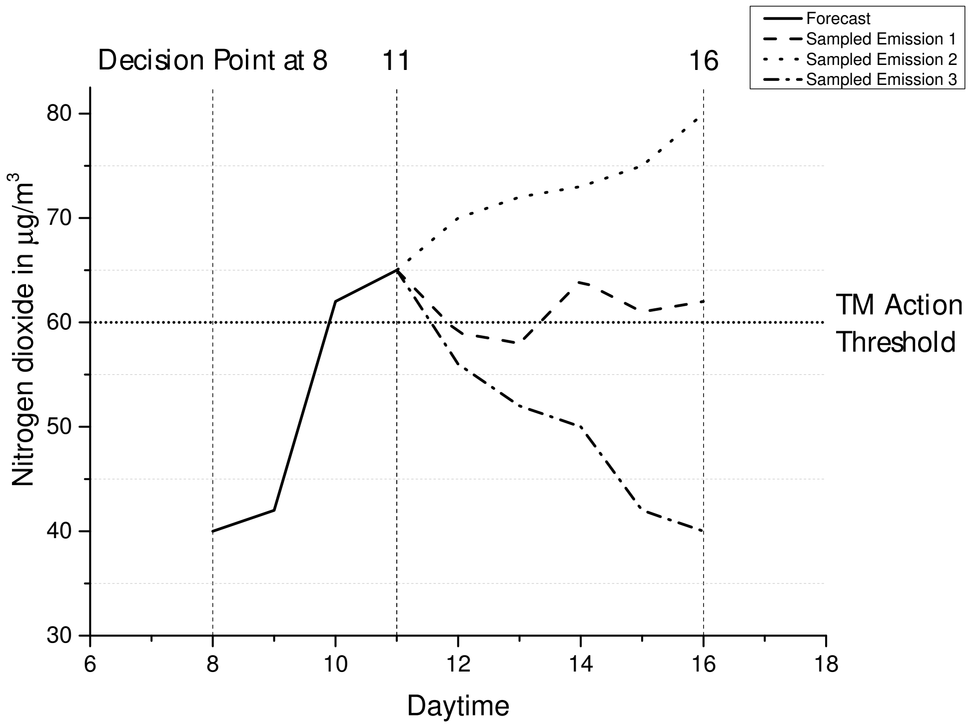


Figure 9.4: Emission Forecast and possible sampled Emission Trajectories (adapted from Köster et al. (2017b))

9.3 Adapted Nearest Insertion For Customer Vehicle Assignment for VRP II

In the VRP II, a number of customer pick-up requests arrive when the delivery fleet has already started their delivery tours. The problem that needs to be solved here is to which vehicle of the fleet a request is assigned and at which position the request is inserted into the sequence of the delivery tour. Therefore, we use an adapted Nearest Insertion method. The Nearest Insertion heuristic is in its pure form a tour construction heuristic and concentrates on only one vehicle with one tour (Rosenkrantz et al. 1977). The customer requests can be seen as nodes in the transport network. An insertion operation places a new node between two other older nodes in the customer delivery sequence. Therefore, the edge that connects the old nodes is removed from the tour plan and is replaced by two new edges which connect the previous nodes with the inserted node. The procedure can, however, also be adapted to insert a node into an already existing tour. Given a set of nodes C and a tour T, which is a subset of C, a node $b \in C$ needs to be inserted in T.

Therefore, algorithm 5 is used. In a tour with four nodes, three insertion options, which are between any two successive sequenced nodes, exist. For the Nearest Insertion heuristics, the increase of travel times for every possible insertion point between two nodes q and w is calculated, where q and w can be any successively arranged nodes in the tour. In the procedure, the replacement edges $e_{q,b}$ and $e_{b,w}$, that replace the previous edge $e_{q,w}$, are searched that minimize the increase in overall tour travel time. This would place the node at the cheapest insertion point between the nodes q and w in the tour T.

Algorithm 5: Nearest Insertion

Input : Node b, Set of Nodes C, Tour T

1 Find edge $e_{q,w}$ in T which minimizes $\tau_{q,b} + \tau_{b,w} - \tau_{q,w}$;

2 Delete edge $e_{q,w}$ and add edges $e_{q,b}$ and $e_{b,w}$ to obtain tour $T = (T, b)$;

As VRP II contains multiple vehicles and multiple dynamic customer pick-up requests, we use an adapted version of the standard Nearest Insertion heuristic. At a decision point k with multiple requests, we calculate the insertion cost for each request in each insertion option of every tour of every vehicle. The costs of the potential insertion times are then ordered. The request that would result in the least increase of travel time is inserted in the respective tour at the respective position. Then, the insertion costs for the remaining customer request candidates are recalculated as the insertion options changed through the last inserted node. Then, the travel time increases are ordered and the cheapest node is again inserted. This is done successively until all requests are inserted.

Part III

Computational Experiments

Chapter 10

Experiment Setup

In our experiments, we vary the availability of traffic management information to simulate different cooperation level between a dynamic traffic management system and a city logistics service provider. Through the evaluation of our experiments, we can discover if and how a CLSP can benefit from a cooperation with the traffic management. Furthermore, we can identify if a dynamic reaction to traffic management actions is required, if routing without a cooperation is sufficient or if traffic management information in general can be ignored in fleet planning. Therefore, we simulate a CLSP fleet in the case study and evaluate the total fleet tour duration that is required to fulfill the fleet's delivery tours. For the traffic management, a desired result of a corporation is achieved when the delivery fleet avoids polluted areas. Therefore, we measure the fleet's time in hot-spots areas where the air pollution traffic strategy is active. In the case study, we use the two different vehicle routing problems, introduce multiple speed scenario settings, which vary the traffic strategy effect on the traffic, and vary the number of delivery vehicles. For the simulation of the case study, a random day from the environmental data is chosen and then for each of the three hot-spots the corresponding individual emission trajectories are used. For all routing decisions, we use the routing solver Spider and vary the inserted customers, the topology and the number of vehicles to investigate the problem formulation of the two different VRPs.

Table 10.1: Customer Service Time depending on Fleet Size in Minutes

Vehicles:	2	3	4	5
Service Times:	15	30	60	60

The service times for a customer district are modeled in relation to fleet size as seen in Table 10.1. The goal was to reach approximately a working time of about eight hours per vehicle. In case of low service times, which indicates a low customer demand per district, a vehicle is able to serve more districts each day. Therefore, less vehicles are required. For example when a customer district has a service time of 15 minutes, only two vehicles are needed to serve the customer districts within approximately eight hours. The service time limit per customer district is set to 60 minutes as this results. Deliveries start at 08:00 in the morning and are expected to finish around 16:00 in the afternoon, but this can vary with the stochastic travel times.

10.1 Training Data Set for the Emission Forecast

The partial time-dependent sampling approach uses historical air pollution data to forecast future emission trajectories. Therefore, a training dataset of 30 days from the Braunschweig hot-spot was used. The dataset has hourly NO_x air-pollution values. For the complete training set, the emission trajectories were analyzed for mean change values and their standard deviations with all data points between 08:00 in the morning and 20:00 in the evening. The results are documented in Table 10.2. For example, between 08:00 and 09:00 (08-09), the standard NO_x air pollution trajectory increased by 9.93 $\mu g/m^3$ with a standard deviation of 7.26 $\mu g/m^3$.

Table 10.2: Average Change of Emissions in Training Dataset in $\mu g/m^3$

Time:	08-09	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18	18-19	19-20
Mean Change:	9.93	-3.12	-9.37	-3.56	1.31	-2.62	1.68	4.31	-1.06	3.50	1.56	3.62
Standard Deviation:	7.26	5.39	6.45	3.78	3.18	6.09	5.83	2.94	3.57	4.62	7.32	6.31

10.2 VRP I Settings

For the VRP I, we can differentiate between five methodical and cooperation level policy variations, which are seen in Figure 10.1. The first row describes the name of the policy and its attributes are structured underneath in rows two and three. Row two indicates the shared information between CLSP and traffic management and the third row shows routing attributes that are used for the test variant. The first three policies analyze how different cooperation levels influence CLSP companies that use static a-priori planned routes. In these cases, we first decide how the customers are

Policy:	*NI - Static*	*CS - Static*	*FI - Static*	*CS - Dynamic*	*FI - Dynamic*
Cooperation:	None	Current Strategy	Current Strategy and Pollution Forecast	Current Strategy	Current Strategy and Pollution Forecast
Routing:	Static - Distance	Static - Current Strategy	Static - PTDS	Dynamic - Current Strategy	Dynamic - PTDS

Figure 10.1: Experiment Structure of VRP I

distributed between the fleet's vehicles and then plan an a-priori delivery tour for each vehicle. The a-priori tours are static and do not allow re-optimization to newly available information. In the simulation, the static tour plan is then affected by the dynamic travel times. For the static a-priori tours, we distinguish between the three traffic management cooperation level, which result in different travel time matrix inputs for the solver. First, we use a policy where no cooperation between CLSP and traffic management happens, which symbolizes how city logistics companies operate today. This policy is called $NI-Static$. Here, the routing and the calculation of the distribution of the freight between the fleet are based on the static edge distances in the network and not on the travel times. The second policy represents a cooperation that transfers the current traffic strategy information ($CS - Static$) and the third policy offers the current and forecasted information ($FI-Static$) to the CLSP. The current information implies that the traffic strategy that is active when the vehicles start their delivery tours is used for distribution of goods between the vehicles and a-priori routing. For the current and forecasted information policy, the partial time-dependent sampling of a travel time matrix as described in Section 9.2 is used for the calculations. In many other routing applications, static a-priori routes have proven not to be the most efficient routing method as dynamic re-routing of delivery vehicles based on new information is beneficial for the objective. This can also be the case for our problem, where the initial distribution of the freight between the fleet vehicles is kept and then the routes are adjusted at decision points according to newly available information. To find out if dynamic re-optimization is required, we institute two re-optimization policies. The first dynamic re-optimization policy uses the current traffic strategy ($CS-Dynamic$) to re-optimize the delivery tours at decision points. $FI - Dynamic$ has information about the current traffic strategy and a short term emission forecast. At each decision point in the dynamic decision making process, the policy first creates a travel time matrix with partial time-dependent sampling and then uses this matrix for the re-optimization with Spider. Furthermore in VRPI, the fleet size is varied between two, three, four and five vehicles.

10.3 VRP II Settings

Policy:	*NI*	*CS*	*FI*
Cooperation:	None	Current Strategy	Current Strategy and Pollution Forecast
Insertion:	Distance	Current Strategy	PTDS
Re-optimization:	No	Yes	Yes

Figure 10.2: Experiment Structure of VRP II

For VRP II, we use three different policies with different cooperation levels and therefore vary the degree of information for decision making. Figure 10.2 shows the three policies NI, CS, FI and their attributes below. NI represents a case where no cooperation is in place, CS represents a case where the current strategy is shared and FI represents the case where current and forecasted information is available for decisions of the CLSP. Each of the three policies uses the adapted nearest insertion procedure from Chapter 9.3. However, to simulate the three cooperation levels, we use the respective distance or travel time matrix that is available to each policy. NI uses the distance matrix, CS incorporates the currently active traffic management strategy into a travel time matrix and FI constructs a travel time matrix with PTDS. As CS and FI have access to traffic strategy information that changes

Table 10.3: City Speed Scenarios with Impact of Dynamic Traffic Management in [km/h]

Traffic Scenarios	Sc1	Sc2	Sc3	Sc4	Sc5
Accelerated street segments	40	40	30	30	30
Standard street segments	25	25	25	25	25
Slowed street segments	5	10	5	10	20

stochastically, they are also allowed to re-optimize their tours based on their information from their cooperation level. The fleet size is set to $k = 2$ and we use five different ratios of dynamic to total customers, which are a DoD of 0.0, 0.2, 0.4, 0.6 and 0.8.

10.4 Traffic Management Impact on Traffic Speed

A traffic strategy has an effect on travel speeds of edges by changing the capacity of a street segment. It can either increase or decrease the speed of a segment. The traffic load of a street segment determines how much the change in capacity results in actual travel time change for this street segment. In general, the closer the amount of traffic on a street segment is to the street segment's capacity limit, the higher is the effect of a traffic strategy on its travel speed. As the amount of traffic is never constant, we also vary the speed changes that are induced by the traffic strategies. Therefore, we introduce speed scenarios, which differentiate themselves in how much a street segment's speed is either accelerated or slowed by a traffic strategy. In total, five speed scenarios exist as seen in Table 10.3. In the table, it can be discovered that the magnitude of the accelerated speeds is not varied as high as the magnitude of slowed speeds. This has been done because accelerating traffic is always limited by the nature of traffic as traffic light controls at intersections have limited control options for accelerating certain traffic flows and laws might restrict speeds. Slowing traffic flows or limiting access to polluted areas is, however, possibly unlimited especially when traffic is heavy and average speeds are reduced to a stop and go behavior.

Chapter 11

Experimental Results and Discussion

This section presents and discusses the results of the computational experiments. Each of the experiments has been run 200 times and the results are averaged in the following tables and graphics. The result chapter is split into two sections. In each of the sections, the results from the experiments for one of the two VRPs are presented and followed by a short discussion.

$$\frac{\pi_{\text{base}} - \pi_{\text{compare}}}{\pi_{\text{base}}} \tag{11.1}$$

To compare different results of the different policies with different cooperation levels between traffic management and logistics, normalized values according to Equation 11.1 are used. The policy π_{base} acts as the baseline to which all other experiments are compared to. In this thesis, π_{base} is represented by the scenario with no cooperation (VRP I: $NI - Static$; VRP II: NI). The policy π_{compare} can stand for any other policy. The equation 11.1 shows in essence the relationship in solution quality of π_{compare} to π_{base}. In the following sections, the normalized values are used to evaluate and compare total delivery travel time of the fleet and hot-spot time. The total delivery time indicates how much time the fleet needs to serve all customers and return to the depot subtracted by the service times of the customers. The hot-spot time represents the total time a fleet spends in hot-spot areas when they are active during their delivery tours. In the graphs and tables in the following, they are indicated as TT for the total delivery travel time and by TM for the hot-spot time.

11.1 Results and Discussion for the Experiments of VRPI

In this section, the results for VRPI are presented and analyzed. The results can be seen in Table 11.1 with normalized values in relation to the base policy $NI - Static$ and in Table 11.2 with absolute values. Excerpts were picked from the results and visualized in figures to easier compare and find trends in the results. Furthermore, the traveled paths of different policies during the delivery tours were analyzed for $NI - Static$, $CS - Dynamic$ and $FI - Dynamic$. The different hot-spot times of $NI - Static$ and $FI - Dynamic$ were compared by overlaying the paths of the two policies and by calculating the usage differences at all hot-spot street segments. Therefore, it can be discovered where and how the different street segments in active hot-spots areas were used.

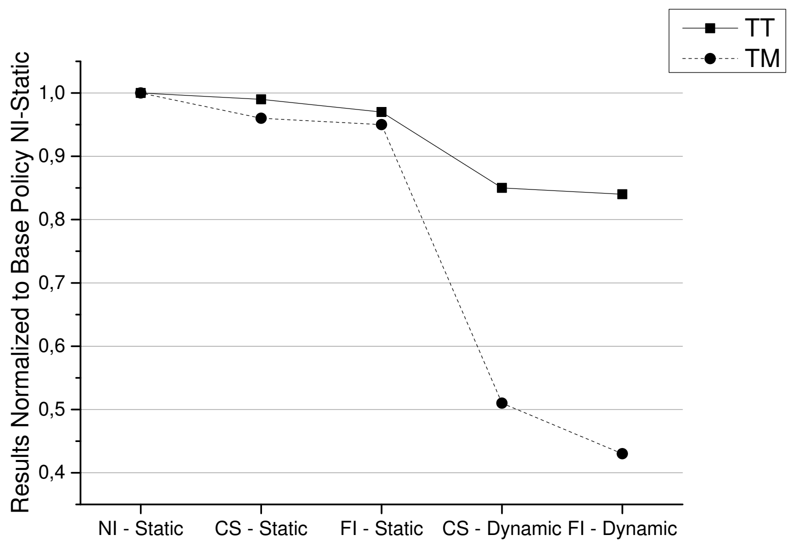
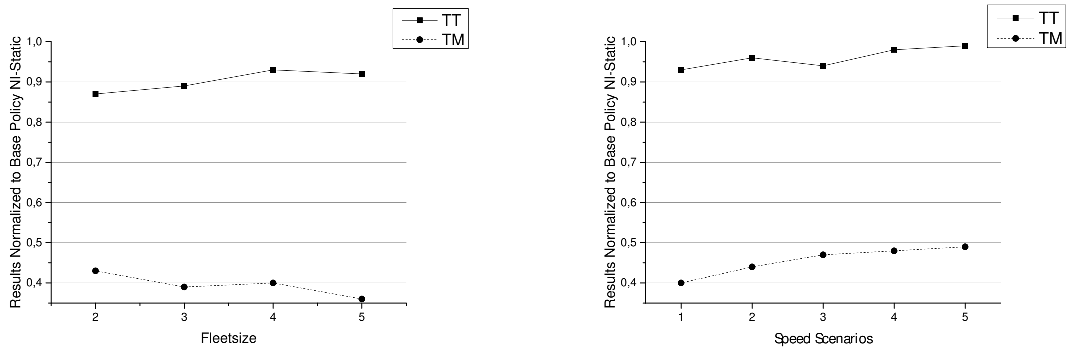


Figure 11.1: Results for VRPI - 2 Vehicles - Speed Scenario 1

Figure 11.1 shows the normalized results of the five policies for the experiments with two vehicles and speed scenario 1. The x-axis differentiates the policies and the y-axis shows the normalization scale to represent how good the solution quality of a policy is in comparison to the base policy. From the evaluation of the experiments each of the policies has a square point for the total delivery travel time duration of the fleet and a round circle for hot-spot time. The base policy $NI - Static$ has the value of 1.0. When comparing the static solutions ($NI - Static$, $CS - Static$ and $FI - Static$), it can be discovered that the solution quality improves with more information through a cooperation. For example, the slight improvement to 0.99 in total delivery travel time can be made by using the current traffic strategy with the $CS - Static$ policy at the start of the day when determining the tours for the vehicles. The hot-spot time drops to 0.96, which is also a slight better improvement over the base policy. For $FI - Static$, the solution quality increases to 0.97 in travel time and 0.95 for hot-spot time. Already for the static policies, it is possible to discover the benefit of the additional traffic management information for logistics activities. The traffic management on the other hand profits percentually even higher through the reduced hot-spot time than the CLSP from the reduced delivery times from a cooperation. The dynamic policies show an improved solution quality compared to the static policies. $CS - Dynamic$ improves the solution in delivery time to 0.85 and to 0.51 in hot-spot time, which is a drastic improvement, especially for the traffic management key performance indicator hot-spot time. The anticipating approach $FI - Dynamic$ further improves delivery time to 0.84 and to a hot-spot time of 0.43 of the base policy. This translates to a decrease of 28.36 minutes in delivery time and 14.56 minutes in hot-spot time. The difference in delivery time between the policies $FI - Dynamic$ and $CS - Dynamic$ seems rather insignificant, but when looking at Table 11.1, it can be discovered that in all experiments $FI - Dynamic$ is either better than or equal to $CS - Dynamic$ in total fleet delivery time solution quality. However when comparing the hot-spot times, $FI - Dynamics$ shows a more reduced hot-spot time. This suggests that using the FI policy does not only reach marginal gains compared to other dynamic routing policies in total delivery time, but it also realizes a higher reduction in hot-spot times.

Figure 11.2a shows the impact of the fleet size for speed scenario 1 and the $FI - Dynamic$ policy. The x-axis shows the different tested fleet sizes and the y-axis shows again the normalized scale. The results of the experiments with the different fleet sizes were normalized to their own base policy. A clear trend be discovered as the solution quality for the total delivery travel time decreases with a growing fleet size. In the two vehicle experiment, the $FI - Dynamic$ policy reaches a normalized value of 0.84 and in the five vehicle experiment the policy only reaches 0.92 compared to its own base policy. A reasonable explanation for this is that, when using fewer vehicles, each vehicle carries the goods for more customers. Therefore, the policy has more routing options to construct an efficient tour. Interestingly,



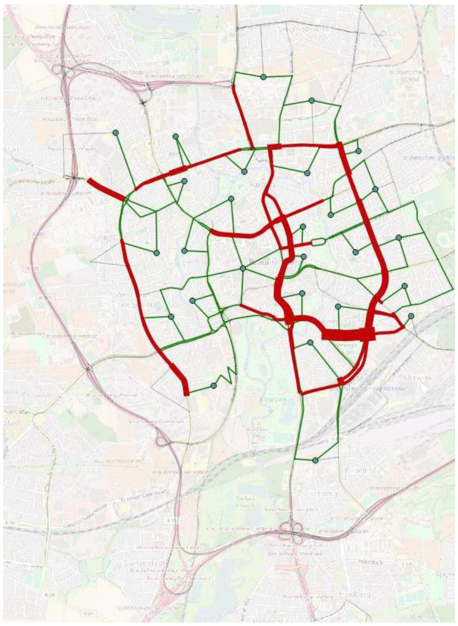
(a) Impact of Fleet Size for Speed Scenario 1 and FI-Dynamic

(b) Impact of Speed Scenarios for FI-Dynamic and 4 Vehicles

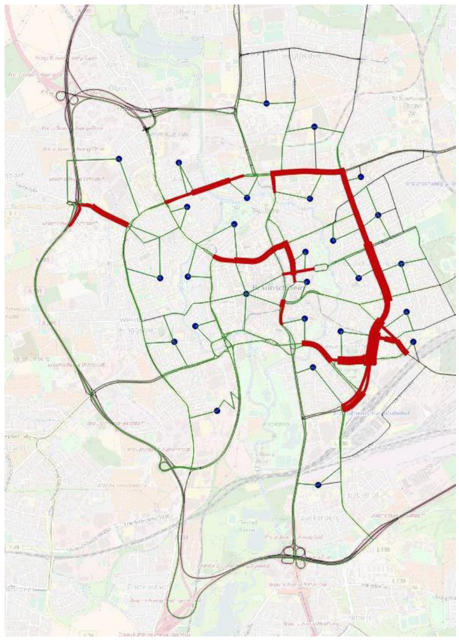
Figure 11.2: Results for VRPI

when looking only at the normalized values of the hot-spot times in the graph, it seems that the $FI - Dynamic$ policy performs better with a increasing fleet size. However, when looking at the absolute values in Table 11.2, it can be discovered that the hot-spot time actually increases from 10.86 minutes for a fleet of two vehicles to 18.34 minutes for a fleet of five vehicles, which is in increase of 68.87%. The hot-spot time of the base policy on the other hand increases from 25.42 minutes to 51.48 minutes, which is an increase of 102.52%. This now seems more logical as the static NI base policy can not evade active hot-spots as it has no knowledge about their activation.

Figure 11.2b shows the impact of the different speed scenarios for the policy $FI - Dynamic$ with a fleet size of four. The x-axis differentiates the five different speed scenarios. Although there is not a linear behavior in the setup of the speed scenarios, in general the induced travel speed changes by traffic management in the active hot-spot areas is higher in speed scenario 1 than in 5 as seen in Table 10.3. In the Figure 11.2b, a trend towards a better solution quality for total delivery and hot-spot time can be discovered for the experiments where the impact of the traffic management on the travel speeds is high. For example, in speed scenario 1, the total delivery travel time reaches a normalized value of 0.94 and the hot-spot time reaches 0.40. In speed scenario 5, the solution quality is worse and reaches values of 0.99 for fleet travel time and 0.49 for hot-spot time. In the graph and most experiments, as seen in Table 11.1, a high improvement can also be discovered for speed scenario 3. This was, however, expected due to the structure of the speed scenarios. When entering hot-spot areas, the speed scenario 3 slows to the same speed as speed scenario 1, but in contrast induces a slower speed inside the hot-spot areas.



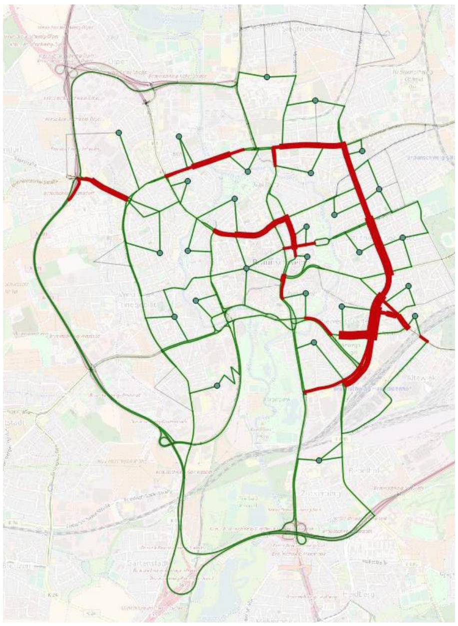
(a) Used Roads and Hot-spot Violations for $NI - Static$



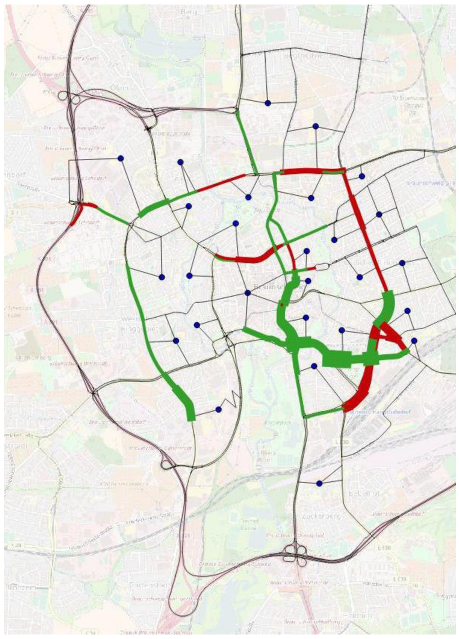
(b) Used Roads and Hot-spot Violations for $CS - Dynamic$

Figure 11.3: Used Roads and Hot-spot Violations for Speed Scenario 1 and a Fleet Size of 2 (Köster et al. 2017b, OpenStreetMap Contribution 2017)

The difference in hot-spot time for the different policies is noticeable. Therefore, additional analyses of the experiments were made with the goal to find out where the advanced policies $FI - Dynamic$ and $CS - Dynamic$ decrease their hot-spot times compared to the base policy $NI - Static$. The Figures 11.3a, 11.3b and 11.4a show the used paths of the delivery fleet for a total of 50 delivery simulations. Each street received a usage counter. If a vehicle traversed an edge, the related counter was increased by one. The streets in the hot-spots have an additional counter that increases when a delivery vehicle used an edge in a hot-area and this hot-spot was active. Each graph has for optical reasons an OpenStreetMap^{TM} background layer of the city of Braunschweig. The customer districts are symbolized by blue dots. The street network is colored in black. This is, however, only visible if the streets were not used by the fleet in the simulation. If a vehicle of a policy variant has used an edge, it is colored in green. The hot-spot violations counter is colored in red. The amount of usage of the streets in hot-spot areas is visualized by their width. Broad red segments were used more often than thin segments. For the base policy



(a) Used Roads and Hot-spot Violations for $FI - Dynamic$



(b) Used Roads and Hot-spot Violations $FI - Dynamic$ over $NI - Static$

Figure 11.4: Used Roads and Hot-spot Violations for Speed Scenario 1 and a Fleet Size of 2 (Köster et al. 2017b, OpenStreetMap Contribution 2017)

$NI - Static$ in Figure 11.3a, it can be seen that the hot-spots in the east, the city center and the west of Braunschweig were violated evenly with a slight focus on hot-spot one and three in the east and in city center. The delivery vehicles stay in the city and are not using the surrounding highway with this policy. The policies $CS - Dynamic$ and $FI - Dynamic$ show a rather similar behavior to each other, except that $FI - Dynamic$ has less hot-spot time violations. Both policies seem to avoid the south-west area of hot-spot one and the area of hot-spot three in the city center when these hot-spots were active. The reason is probably that both policies use the surrounding highway to avoid the active hot-spots.

Figure 11.4b shows the difference between the base policy $NI - Static$ and $FI - Dynamics$. In this figure, the hot-spot violation counters were subtracted from each other to see where $FI - Dynamics$ achieves a lower hot-spot counter. Therefore, only street segments that belong to a hot-spot area are colored. Green colored edges represent a lower hot-spot counter for this edge of $FI - Dynamic$ and red relates to a higher hot-spot counter of $FI - Dynamics$. The widths of the red and green colored edges relate to amount of the difference between the policies in

Table 11.1: Normalized Results to NI - Static for VRPI

Vehicles:	2									
Speed Scenario:	1		2		3		4		5	
Evaluation:	TT	TM	TT	TM	TT	TM	TT	TM	TT	TM
NI - Static	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CS - Static	0.99	0.96	0.99	0.97	0.99	1.00	0.99	0.98	0.99	0.99
FI - Static	0.97	0.95	0.99	0.98	0.97	0.98	0.99	1.00	0.99	1.03
CS - Dynamic	0.85	0.51	0.94	0.56	0.87	0.52	0.94	0.55	0.95	0.49
FI - Dynamic	0.84	0.43	0.93	0.51	0.85	0.52	0.94	0.52	0.94	0.46
Vehicles:	3									
Speed Scenario:	1		2		3		4		5	
Evaluation:	TT	TM	TT	TM	TT	TM	TT	TM	TT	TM
NI - Static	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CS - Static	0.97	1.02	0.99	0.98	1.00	1.02	1.00	0.92	1.00	0.97
FI - Static	0.97	1.00	0.98	0.98	0.97	0.98	0.99	1.01	0.98	0.96
CS - Dynamic	0.89	0.45	0.96	0.47	0.92	0.60	0.98	0.51	0.97	0.53
FI - Dynamic	0.89	0.39	0.96	0.41	0.90	0.47	0.97	0.51	0.97	0.49
Vehicles:	4									
Speed Scenario:	1		2		3		4		5	
Evaluation:	TT	TM	TT	TM	TT	TM	TT	TM	TT	TM
NI - Static	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CS - Static	0.99	1.02	0.99	1.01	1.00	1.02	1.00	0.95	1.00	0.97
FI - Static	0.99	1.05	0.98	1.01	0.98	0.98	0.99	0.95	1.00	1.00
CS - Dynamic	0.93	0.49	0.96	0.49	0.95	0.60	0.98	0.52	0.99	0.49
FI - Dynamic	0.93	0.40	0.96	0.44	0.94	0.47	0.98	0.48	0.99	0.49
Vehicles:	5									
Speed Scenario:	1		2		3		4		5	
Evaluation:	TT	TM	TT	TM	TT	TM	TT	TM	TT	TM
NI - Static	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CS - Static	0.99	1.01	1.00	1.01	1.01	1.04	1.00	0.98	1.00	0.94
FI - Static	0.99	0.99	1.00	1.03	0.99	1.01	0.99	0.98	1.00	0.98
CS - Dynamic	0.93	0.43	0.98	0.50	0.95	0.51	0.98	0.49	0.99	0.46
FI - Dynamic	0.92	0.36	0.98	0.46	0.94	0.44	0.98	0.46	0.99	0.46

Table 11.2: Absolute Result Values for VRPI in minutes

Vehicles:	2									
Speed Scenario:	1		2		3		4		5	
Evaluation:	TT	TM	TT	TM	TT	TM	TT	TM	TT	TM
NI - Static	180.06	25.42	157.44	25.52	181.06	33.70	157.49	26.00	153.89	34.59
CS - Static	177.42	24.31	155.21	24.84	178.66	33.86	156.21	25.58	151.75	34.07
FI - Static	174.76	24.11	155.72	25.16	176.27	32.97	156.00	25.95	151.91	35.51
CS - Dynamic	153.89	13.01	148.20	14.31	158.04	17.69	148.22	14.21	145.90	16.92
FI - Dynamic	151.7	10.86	147.01	13.13	154.54	17.37	148.09	13.60	145.04	15.78
Vehicles:	3									
Speed Scenario:	1		2		3		4		5	
Evaluation:	TT	TM	TT	TM	TT	TM	TT	TM	TT	TM
NI - Static	251.21	36.97	228.59	36.51	250.92	36.26	228.79	35.12	229.46	34.26
CS - Static	244.16	37.80	226.31	35.60	249.81	37.02	229.71	32.27	229.02	33.26
FI - Static	243.93	36.96	224.69	35.87	242.95	35.63	226.60	35.33	225.90	33.01
CS - Dynamic	224.56	16.62	220.31	17.18	231.56	21.75	224.34	17.93	223.42	18.03
FI - Dynamic	223.80	14.45	218.46	14.80	226.32	17.13	222.1	18.01	221.51	16.71
Vehicles:	4									
Speed Scenario:	1		2		3		4		5	
Evaluation:	TT	TM	TT	TM	TT	TM	TT	TM	TT	TM
NI - Static	414.61	38.42	388.11	38.52	412.78	36.21	389.61	32.04	382.61	40.42
CS - Static	411.73	39.18	387.12	39.07	413.04	37.05	387.73	30.55	383.80	39.19
FI - Static	411.23	40.35	386.42	38.78	406.41	35.63	386.71	30.39	381.81	40.28
CS - Dynamic	387.65	18.91	381.17	18.77	391.73	21.75	382.18	16.56	379.55	19.86
FI - Dynamic	384.41	15.51	379.71	16.83	385.99	17.13	381.49	15.53	377.80	19.73
Vehicles:	5									
Speed Scenario:	1		2		3		4		5	
Evaluation:	TT	TM	TT	TM	TT	TM	TT	TM	TT	TM
NI - Static	501.11	51.48	461.94	37.81	487.81	39.74	467.60	47.31	455.41	42.35
CS - Static	497.57	52.11	459.67	38.02	492.37	41.41	466.81	46.22	453.28	39.70
FI - Static	495.11	51.02	459.83	38.98	482.96	40.03	464.69	46.48	454.66	41.41
CS - Dynamic	463.86	22.09	452.68	18.82	464.12	20.29	457.69	23.28	450.50	19.59
FI - Dynamic	459.19	18.34	452.04	17.37	458.69	17.49	456.29	21.77	450.78	19.47

hot-spot time. Thin colored edges only have a small difference, whereas broader colored edges represent cases were the difference is more significant. The figure shows that $FI - Dynamic$ has a slightly higher hot-spot time in the area of hot-spot four, especially in the northern and southern part of this hot-spot. Keep in mind that the depot is in this area and some hot-spot time can not be avoided when starting or ending a delivery tour. The violations in the southern part indicate that in cases of an activation the vehicles divert to the highway. A significant difference can be spotted in the city center at hot-spot three except for small part of the east-west connection and in the area between the outer-city ring and city center. This area partly belongs to hot-spots three and four. The hot-spot area around hot-spot one, especially the complete west part of the outer ring, shows a significant reduction in the hot-spot counter for $FI - Dynamics$.

The benefit of traffic management information for an incorporation into dynamic routing policies for a CLSP that is confronted with a delivery problem has been proven with the experiments of VRPI. The dynamic policies with traffic management information perform better than the static policies with or without traffic management information. For example, when planning the delivery tours with the policy $FI - Dynamic$, the delivery time for speed scenario one and two vehicles is on average 28.36 minutes faster, which is 16% lower than the static base policy $NI - Static$. Considering that the highest cost is attributed to the last-mile in city logistics, then this result represents a significant saving for a CLSP and warrants the pursuit of a cooperation with the traffic management. The policy $FI - Dynamic$ is only slightly better than the policy $CS - Dynamic$. This slight gain might be offset by the additional technological infrastructure to implement the $FI - Dynamic$ policy with the more complicated PTDS approach. However, the higher improvement of $FI - Dynamic$ in hot-spot time is desirable for the traffic management. By sharing information the hot-spot time was reduced by 57%. When keeping in mind that all urban logistics activities are a significant share of the traffic, this would result in a much lower traffic burden at the hot-spots. Consequently for the presented case of VRPI, a cooperation between traffic management and logistics results in a mutual benefit.

11.2 Results and Discussion for the Experiments of VRPII

In this section, the results for the experiments for VRPII are presented. In VRPII, a city logistics service provider has to serve a number of known customers and incorporate additional mandatory dynamic customer requests into the delivery tours of his fleet. In the experiments, three policies according to the three different cooperation levels are compared. The base policy NI inserts new customer requests based on static edge distances of the city network. This represents the case where no information from the traffic management is available and consequently no cooperation is in place. The policy CS uses the current strategy information and the policy $FI - Dynamic$ uses the more sophisticated PTDS approach. Therefore, these last two approaches require a cooperation with the traffic management. The results are presented in two tables. Table 11.3 shows the results of the experiments, which are normalized to the base policy and Table 11.4 shows the results in absolute values. The impact of the traffic management on travel speeds is varied through the speeds scenarios as in VRPI. Furthermore, the relation of dynamic customer requests to total customers, the DoD, is varied in 0.2 steps between 0.0 and 0.8.

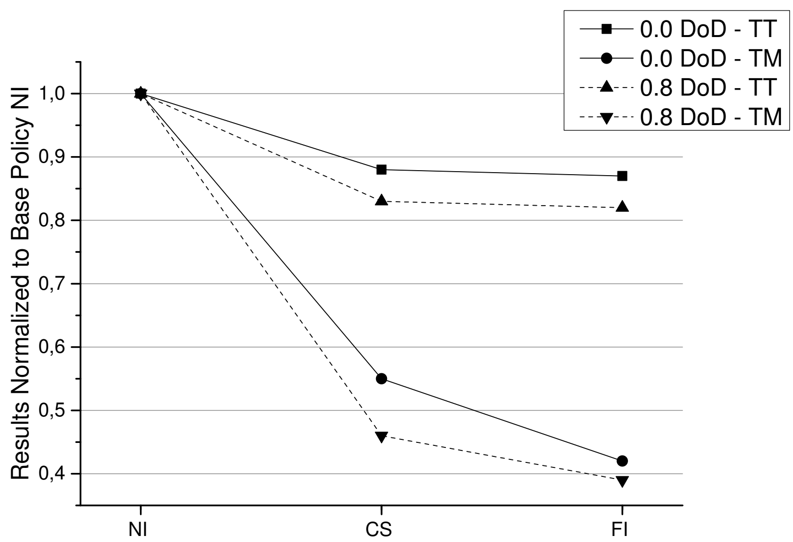
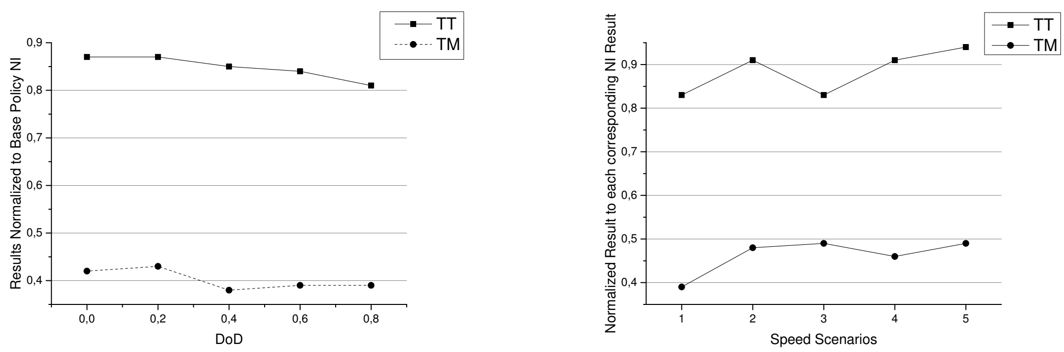


Figure 11.5: Results for VRPII with Speed Scenario 1 and two different DoDs - Speed Scenario 1

Figure 11.5 compares the results of the three policies. The y-axis shows the normalization scale and the different policies are assigned to the x-axis. In the figure, the results for the experiments with speed scenario 1 and a DoD of 0.0 and 0.8 are presented. The total delivery time and the hot-spot time are evaluated. The policies that require a traffic management cooperation improve the solution quality for both performance indicators compared to the base policies. The policy CS improves the delivery travel time to 0.88 for a DoD of 0.0 and to 0.83 for a DoD of 0.8. This results is further improved by the FI policy, which achieves a solution quality of 0.87 for a DoD of 0.0 and 0.81 for a DoD of 0.8. This would decrease the delivery times by 19%, which translates to 48.01 minutes of saved delivery time per day. A similar result can be observed for the hot-spot time. Here, the improvements are larger compared to the base policy and the difference in solution quality between CS and FI is larger as well. For example, the hot-spot time is improved to 0.46 by CS and to 0.39 for the experiment with a DoD of 0.8.

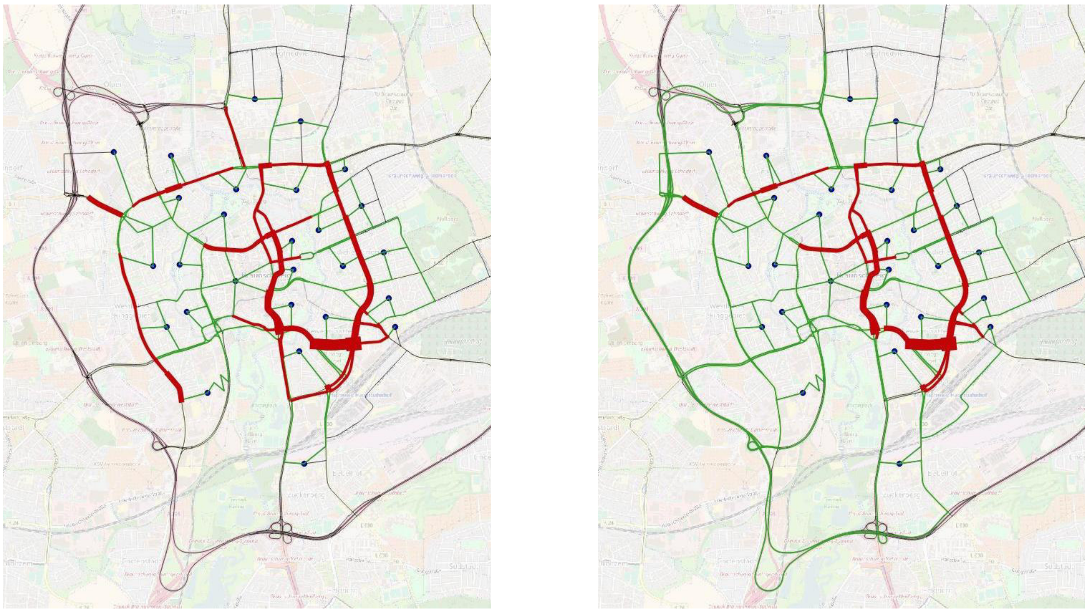


(a) Impact of DoD for Speed Scenario 1 and FI

(b) Impact of Speed Scenarios for FI and DoD of 0.8

Figure 11.6: Results for VRPII

Figure 11.6a shows the influence of different DoD cases for speed scenario 1 with FI as the routing policy. The y-axis shows the normalization scale and x-axis the DoD steps. It can be discovered that the solution quality compared to the base policy increases when the DoD rises especially for the total delivery travel time, but also for the hot-spot time. With a high DoD, the policy has a smaller customer pool per vehicle from which the next customer is chosen. This results in longer distances between customers and delivery vehicles that are routed by the FI policy are more able to avoid active hot-spots with their traffic strategy information and the emission forecast. Figure 11.6b shows the influence of the different speed scenarios for the experiments with FI. In general, scenario 1 has a higher traffic management impact on travel speed than scenario 5. However, as discussed earlier the speed scenario steps do not have linear behavior. In the presented graph, a trend can be discovered for the total delivery travel time and the hot-spot time. The solution quality of FI compared to the base policy increases with a growing traffic management impact on travel speeds in active hot-spot areas. Notably, the speed scenario three has the same solution quality as scenario one for total delivery travel time. Keep in mind that scenario 3 has the same slower speed for entering hot-spot areas as scenario one, only the speed inside the hot-spots areas is different. Consequently for the performance of a cooperational policy compared to its base policy, the traffic speeds in front of the hot-spots are more important.

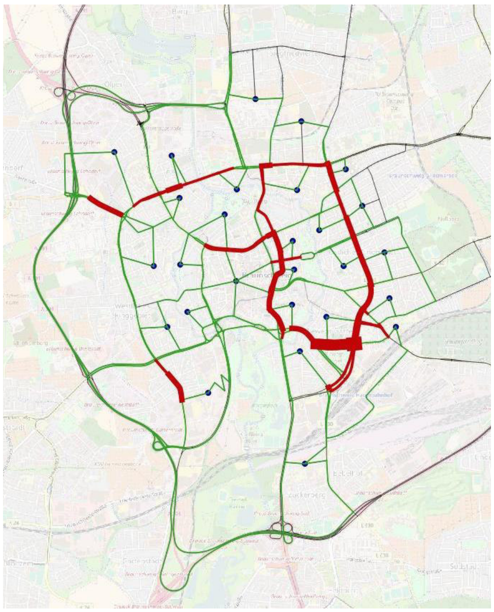


(a) Used Roads and Hot-spot Violations for NI

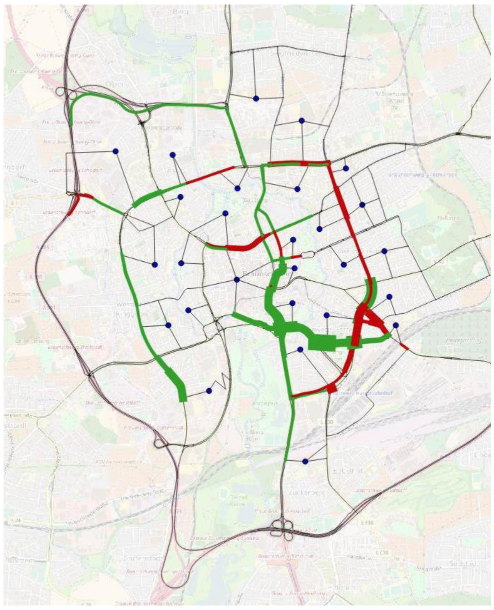
(b) Used Roads and Hot-spot Violations for CS

Figure 11.7: Used Roads and Hot-spot Violations for VRP2, a DoD of 0.8 and Speed Scenario 1 (Köster et al. 2017b, OpenStreetMap Contribution 2017)

The used paths of the different policies are presented in Figure 11.7a, 11.7b and 11.8a in the same style as in the related figures in Section 11.1 for VRPI. Figure 11.7a shows the used paths for the base policy NI. The graph indicates that NI did not use the highway and violated all hot-spots. Especially, it shows a high number of violations in the southeast in the area of hot-spot four and three in the city center. The used paths of CS in Figure 11.7b display that the CS policy used the highway



(a) Used Roads and Hot-spot Violations for FI



(b) Used Roads and Hot-spot Violations FI over NI

Figure 11.8: Used Roads and Hot-spot Violations for VRP2, a DoD of 0.8 and Speed Scenario 1 (Köster et al. 2017b, OpenStreetMap Contribution 2017)

to avoid active hot-spots. This is especially true in the southern part of hot-spot one which is in the west of the city. The streets in the hot-spot areas of hot-spot three and four (city center and east ring) were both used when their associated hot-spots were active. An increased hot-spot time can be discovered between the southeast of the city and the city center. This, however, is because of the depot location, which forces delivery vehicles to travel through the active hot-spot in this area. For the policy FI in 11.8a, nearly the same behavior with small differentiations in the southern part of the hot-spot area one can be seen. Here, a small amount of hot-spot time occurs.

Figure 11.8b directly compares the differences of NI and FI at the hot-spots through a violation counter for each policy and each edge. The violation counter was increased by one when a delivery of a policy used it. The violation counter of FI was subtracted from NI. Therefore a positive value, represented with green color, relates to less hot-spot time of FI for a street segment in a hot-spot area. A negative value relates to more hot-spot time for FI in comparison to the base policy NI. As in the VRPI, the width of an element indicates the severity of hot-spot time difference. A reduction of hot-spot time for the policy FI in the area of hot-spot one can be seen, because delivery vehicles elude to the highway on the way to or from the depot. A significant reduction of hot-spot time can be discovered in the area that is leading from the southeast to the city center and is partly belonging to hot-spot three and four. However, in contrast to VRPI, the east ring of hot-spot four has a slightly different behavior with more hot-spot time. One reason for this is that with dynamic customer requests, the policy has a smaller customer pool for the routing of each vehicle as some requests arrive at a later time. Consequently, the distances between subsequent customer stops are larger. The FI policy with the traffic management information can easier avoid slower active hot-spot areas in case of longer distances between customers, than with shorter distances as not many avoidance options exist. Furthermore, when taking into account that the hot-spot areas discourage entering a hot-spot by decreasing the speed of incoming traffic and that inside a hot-spot the travel speeds are accelerated to remove stop-go behavior, it might be that with longer distances between customer stops, the negative travel time loses of entering an active hot-spot area are partly negated by the accelerated traffic speeds inside the hot-spot areas.

In this section, the usefulness of cooperation between traffic management and a CLSP was examined for a logistics application with dynamic customer requests. The three different cooperation level were represented by three routing policies. For this application, an even higher benefit than for the VRPI application was found. The FI routing policy was able to decrease its total delivery travel time by up to 19%, which translated to a saving of 48.01 minutes. The CS policy also shows a significant decrease in this category. However, the difference between using a dynamic policy with the current traffic strategy information and additional anticipated/forecasted information is higher than in VRPI. Therefore, a cooperation between a CLSP and traffic management, especially with a transfer of forecasted emission information, results in a higher financial gain through more efficient delivery tours for the CLSP. The traffic management profits in return from reduced hot-spot time of the logistics freight traffic. Therefore, a cooperation between logistics and traffic management would result in a mutual benefit for the involved parties.

Table 11.3: Normalized to NI - Static for VRPII

Evaluation:		TT			TM		
Speed Scenario	DoD	NI - Static	CS - Dynamic	FI - Dynamic	NI - Dynamic	CS - Dynamic	FI - Dynamic
1	0.0	1	0.88	0.87	1	0.55	0.42
	0.2	1	0.88	0.87	1	0.50	0.43
	0.4	1	0.87	0.85	1	0.46	0.38
	0.6	1	0.87	0.84	1	0.48	0.39
	0.8	1	0.83	0.81	1	0.46	0.39
Evaluation:		TT			TM		
Speed Scenario	DoD	NI - Static	CS - Dynamic	FI - Dynamic	NI - Dynamic	CS - Dynamic	FI - Dynamic
2	0.0	1	0.95	0.94	1	0.54	0.50
	0.2	1	0.93	0.93	1	0.50	0.47
	0.4	1	0.94	0.94	1	0.46	0.46
	0.6	1	0.93	0.92	1	0.48	0.44
	0.8	1	0.91	0.91	1	0.44	0.48
Evaluation:		TT			TM		
Speed Scenario	DoD	NI - Static	CS - Dynamic	FI - Dynamic	NI - Dynamic	CS - Dynamic	FI - Dynamic
3	0.0	1	0.89	0.87	1	0.63	0.47
	0.2	1	0.88	0.85	1	0.50	0.47
	0.4	1	0.87	0.86	1	0.43	0.41
	0.6	1	0.86	0.85	1	0.49	0.39
	0.8	1	0.83	0.83	1	0.54	0.49
Evaluation:		TT			TM		
Speed Scenario	DoD	NI - Static	CS - Dynamic	FI - Dynamic	NI - Dynamic	CS - Dynamic	FI - Dynamic
4	0.0	1	0.96	0.95	1	0.49	0.52
	0.2	1	0.96	0.95	1	0.57	0.54
	0.4	1	0.95	0.94	1	0.46	0.46
	0.6	1	0.93	0.93	1	0.42	0.41
	0.8	1	0.91	0.91	1	0.47	0.46
Evaluation:		TT			TM		
Speed Scenario	DoD	NI - Static	CS - Dynamic	FI - Dynamic	NI - Dynamic	CS - Dynamic	FI - Dynamic
5	0.0	1	0.97	0.97	1	0.46	0.49
	0.2	1	0.96	0.96	1	0.50	0.52
	0.4	1	0.96	0.96	1	0.46	0.44
	0.6	1	0.95	0.95	1	0.46	0.47
	0.8	1	0.94	0.94	1	0.50	0.49

Table 11.4: Absolute Result Values for VRPII in minutes

Evaluation:		TT			TM		
Speed Scenario	DoD	NI - Static	CS - Dynamic	FI - Dynamic	NI - Dynamic	CS - Dynamic	FI - Dynamic
1	0.0	174.97	153.123	151.55	27.13	14.8	11.41
	0.2	185.10	161.98	161.94	32.56	16.21	14.06
	0.4	193.9	167.83	165.40	39.96	18.37	15.06
	0.6	215.31	186.72	181.85	37.43	19.93	14.52
	0.8	253.42	209.74	205.41	49.44	22.50	19.39
Evaluation:		TT			TM		
Speed Scenario	DoD	NI - Static	CS - Dynamic	FI - Dynamic	NI - Dynamic	CS - Dynamic	FI - Dynamic
2	0.0	155.07	147.62	146.48	28.43	15.49	14.25
	0.2	167.41	155.04	154.89	36.73	18.33	17.33
	0.4	171.05	161.33	160.00	29.55	13.66	13.49
	0.6	195.21	181.82	179.94	44.06	21.20	19.39
	0.8	226.16	206.10	205.18	57.03	26.68	26.15
Evaluation:		TT			TM		
Speed Scenario	DoD	NI - Static	CS - Dynamic	FI - Dynamic	NI - Dynamic	CS - Dynamic	FI - Dynamic
3	0.0	178.09	157.67	154.26	29.23	18.53	13.88
	0.2	186.28	164.65	159.03	36.73	18.33	17.33
	0.4	194.23	169.54	167.96	31.66	13.72	12.85
	0.6	216.9	186.38	184.87	35.30	17.14	13.94
	0.8	252.01	210.36	208.98	50.56	27.14	24.65
Evaluation:		TT			TM		
Speed Scenario	DoD	NI - Static	CS - Dynamic	FI - Dynamic	NI - Dynamic	CS - Dynamic	FI - Dynamic
4	0.0	154.76	148.57	147.60	29.83	14.61	15.41
	0.2	163.02	156.91	155.26	28.75	16.31	15.45
	0.4	172.99	163.81	162.97	29.50	13.66	13.49
	0.6	199.97	185.88	185.11	48.86	20.61	20.16
	0.8	226.16	206.11	205.18	57.15	26.68	26.15
Evaluation:		TT			TM		
Speed Scenario	DoD	NI - Static	CS - Dynamic	FI - Dynamic	NI - Dynamic	CS - Dynamic	FI - Dynamic
5	0.0	147.47	143.29	143.35	33.8	15.69	16.49
	0.2	157.99	152.10	150.97	29.50	14.85	15.44
	0.4	167.67	161.67	160.84	36.76	16.98	16.31
	0.6	186.56	177.51	177.7	44.05	20.32	20.69
	0.8	212.88	199.40	200.1	54.13	27.22	26.69

Part IV

Conclusion and Outlook

Chapter 12

Conclusion and Outlook

This dissertation investigates the usefulness of a cooperation between traffic management and logistics. The investigation focuses on a dynamic environmental-sensitive traffic management system and on city logistics. Therefore, Part I first shows the challenges and opportunities for city logistics service providers in the highly competitive last-mile delivery market and furthermore shows how dynamic environmental-sensitive traffic management systems can help to reduce air pollution in critical hot-spot areas by influencing traffic flows and therefore travel speeds through traffic strategies. Part II introduces a case study for a city logistics service provider in an urban environment with three hot-spots. The traffic flows around the hot-spot are influenced by a dynamic environmental-sensitive traffic management system. This results in stochastic travel times for the city logistics service provider. The findings of the case study are presented in Part III.

The structure of this thesis and motivation for a cooperation between traffic management and logistics is presented in Chapter 1. The motivation for a city logistics service company is a reduction in operational costs for their deliveries by reducing fleet and workforce time. For the traffic management the motivation is that freight vehicles could avoid traveling through hot-spot areas when the air pollution is critically high.

Chapter 2 shows that the amount of urban freight traffic is growing and that one of the main drivers for this trend is the e-commerce. The chapter describes furthermore what the term *city logistics* means and who the stakeholders in this environment are. Finally, the chapter explains the complexity of last-mile deliveries and why city logistics need specific delivery concepts.

The transportation problems of logistics companies can be modeled and solved with operations research methods. The results are most of the time significantly better than hand-picked solutions. Chapter 3 presents the vehicle routing problem with an exemplified problem, the specific inputs for city logistics models and why anticipation of future events can be highly beneficial.

Chapter 4 presents the currently available related research literature for vehicle routing problems. The increase of city logistics publications is shown and described. The chapter shows that the presented research question of this dissertation has not been studied yet and how it differentiates itself from other research.

Traffic management is a tool of municipalities to organize road traffic. Dynamic traffic management systems can dynamically adapt their infrastructure with traffic strategies to influence traffic flows. Chapter 5 describes the goals of traffic management, why air pollution and traffic congestion are problematic, how dynamic systems can reduce these problems and how this can be modeled.

Within Chapter 6, the theoretical benefits of a cooperation between logistics companies and traffic management systems are presented in an introductional example, which is a simplified version of the case study. It is described why and how the case study is modeled as a *Dynamic Vehicle Routing Problem with Stochastic Matrix Changes*. For the case study, three different cooperation levels are distinguished:

- No cooperation
- The current state of traffic strategies is shared with the city logistics service provider
- The current state of traffic strategies and a 3 hour emission forecast are shared with the city logistics service provider

The three different cooperation levels allow different routing policies and it is differentiated between static policies, re-optimizing dynamic policies and dynamic anticipating policies.

The case study with an environmental-sensitive traffic management system and the underlying network is presented in detail in Chapter 7. Braunschweig is a typical European city with ring roads around a single city center. The air pollution is critical in three hot-spot areas, which do not comply with the EU air pollution limit. When the air pollution exceeds a NO_2 threshold value, the traffic management changes the traffic infrastructure, i.e. the traffic signals, to reduce the traffic flow into the hot-spot areas. Furthermore, the chapter details the three hot-spots and the air pollution data set that is used in the experiments to simulate the air pollution in the experiments.

In order to simulate the case study, a two-layered architecture for the model is required and presented in Chapter 8. The traffic management system needs a model with a network of single street segments as individual street segment are influenced by traffic management actions. The vehicle routing model requires a network with aggregated edges on a customer/depot level. Furthermore, the chapter presents two different vehicle routing problems with slightly different tasks, which are used to investigate the research question of this thesis from different angles. VRPI has to serve a set of known customer and VRPII receives dynamic customer requests during the day that must be accepted.

In Chapter 9, the routing software Spider that is used for the routing decisions is presented. The developed method partial time-dependent sampling, which allows anticipation within the framework of standard commercial solvers, and an adapted nearest insertion method to distribute dynamic customer requests are presented.

The setup of the computational experiments is presented in Chapter 10 and describes the variations to the fleet size and the routing policies with different cooperation level. Additionally, five different speed scenarios, which represent different impacts of traffic strategies on travel times, and a training set for forecasting emissions within the partial time-dependent sampling approach is presented.

The results of the case study experiments are analyzed in Chapter 11. The VRPs are evaluated for total delivery time, a performance indicator for city logistics service providers, and hot-spot time, a performance indicator for the traffic management, which describes how much time the delivery fleet spends in active hot-spots. The benefit of the cooperation can be discovered over all variations of the experiments.

Furthermore, the results are visualized on a street segment level to see where the more advanced routing policies with traffic management information save hot-spot time.

This dissertation reached the following contribution with the analysis of a cooperation between traffic management and logistics:

- This work is the first to investigate the effects of cooperation between traffic management and logistics.
- A challenging case study was used to investigate the problem. The problem was modeled as a *Dynamic Vehicle Routing Problem with Stochastic Matrix Changes*, which is a new category of vehicle routing problems.
- The method Partial time-depending sampling was presented and allows anticipation in the framework of standard commercial solver.
- In the case study, the total delivery travel time was improved by the anticipating *FI* policy, which has access to current traffic strategy and emission forecast through a cooperation, by up to 16% and 28.36 minutes for VRPI and for VRPII by up to 19% and 48.01 minutes. The hot-spot time of the delivery freight vehicles was lowered by 57% for VRPI and by up to 61% for VRPII. These values are a significant improvements in both performance categories and show the mutual benefit of a cooperation for traffic management and logistics.
- The benefit for the involved parties is higher when more information is shared through a cooperation.
- The sophisticated routing policies with traffic management information avoid hot-spots by using alternative routes.
- The mutual benefit for both parties is high, when the impact of the traffic management on travel speeds in the hot-spot areas is high.
- The results of the experiments show that a cooperation is more useful for logistics applications with dynamic customer requests, which have a high DoD.

This work is the first that investigates a cooperation between traffic management and logistics. The used model is already a sophisticated approach, but the accurateness could be improved in the future by integrating historical floating car data in combination with the use-patterns of the traffic management's traffic strategies from the same time span. Another approach would be to model the presented problem in a micro traffic simulation, where it is possible to model each traffic signal and the city traffic. The results of this dissertation were achieved by a case study with the environmental traffic management system in Braunschweig. In the future other systems in different cities with different street network geometries could be tested to see if the same results are achieved or if the results of this dissertation dependent on the layout of this case study. Furthermore, the scope could be advanced to dynamic traffic-responsive traffic management systems.

Chapter 13

Summary

Today, logistics and traffic management are two important elements for the urban population. Logistic service providers enable the availability of consumer goods to city residents and the traffic management optimizes traffic flows of the city by operating the traffic infrastructure (i.e. traffic signals). This dissertation investigates if logistics and traffic management can achieve a mutual benefit through an information sharing cooperation. The main motivation for a logistics company, which operates in the high cost pressure delivery industry, is a possible reduction of operational costs for their delivery fleet. The motivation of the traffic management to enter a cooperation is a possible reduction of the high traffic burden induced by freight vehicles. In such a cooperation the traffic management could transfer information about the state of the operable traffic infrastructure, and therefore their related current travel time impact, to the logistics company. With this information the logistics company can optimize their delivery tours. This dissertation assesses the benefits of cooperation by analyzing how the delivery tours can be improved and how the freight traffic burden can be reduced. This question is investigated in a case study of an environmental-sensitive traffic management system in the city of Braunschweig, Germany and a city logistics service provider. The air pollution in Braunschweig does not comply with the EU air pollution limit. If the air pollution is high in a hot-spot area, the traffic management changes the traffic infrastructure to reduce the traffic flow into the hot-spot areas, which affects the surrounding traffic situation. In the case study, the degree of information from the traffic management and the tasks of the logistics company are varied and formulated in different dynamic Vehicle Routing Problems. The evaluation of the case study shows that a mutual benefit of the cooperation can be discovered over all variations of the experiments.

Chapter 14

Zusammenfassung

Der kontinuierlich wachsende E-Commerce führt weltweit zu in einem erhöhten innerstädtischen Frachtverkehr. Dieser Frachtverkehr wird von Logistikdienstleister durchgeführt, die einzelne Frachtsendungen zu Auslieferungstouren bündeln. Aufgrund von schwankenden Fahrzeiten im innerstädtischen Umfeld ist eine effiziente Planung der Auslieferungstouren für die Lieferfahrzeuge jedoch schwierig. Um die Verkehrssituation zu verbessern setzten viele Städte Verkehrsmanagementsysteme ein. Diese optimieren den Verkehr durch die Anpassung der Verkehrsleitstrategie an die Verkehrssituation. Diese Dissertation untersucht, ob eine Kooperation zum Austausch von Informationen zwischen einem Logistikdienstleister und dem Verkehrsmanagement die jeweiligen Interessen verbessert. Aufgrund des hohen Kostendrucks der Logistikbranche ist ein Logistikdienstleister an der Verkehrsleitstrategie interessiert um damit die Kosten ihrer Touren zu senken. Das Verkehrsmanagement erhofft sich eine Verminderung der Verkehrsbelastung durch den Frachtverkehr. Der Nutzen einer Kooperation wird in einer Fallstudie mit dem umweltorientierten Verkehrsmanagement in Braunschweig und einem Paketdienstleister analysiert. Dafür wird die Aufgabenstellung des Paketdienstleisters als dynamisches Vehicle Routing Problem, in dem das Verkehrsmanagement die Fahrzeiten beeinflusst, formuliert und mit unterschiedlichen Methoden gelöst. In den Experimenten wird der Einfluss der Verkehrsleitstrategien auf die Fahrzeiten, die Anzahl der Fahrzeuge in der Logistikflotte und zwei Variationen des dynamischen Vehicle Routing Problems betrachtet. Aus den Ergebnissen ist ersichtlich, dass eine Kooperation zwischen Logistikdienstleister und Verkehrsmanagement als sinnvoll zu erachten ist, da sie zu einer Reduktion in der Verkehrsbelastung durch Frachtverkehr in kritischen Bereichen und zu einer Reduktion der Fahrzeiten der Auslieferungstouren führt.

Bibliography

2008. Carbon offsets the u.s. voluntary market is growing, but quality assurance poses challenges for market participants. http://www.gao.gov/new.items/d081048.pdf. Accessed: 2017-05-16.

Agency, European Environment. 2015a. Air quality in europe — 2015 reports. http://www.eea.europa.eu/publications/air-quality-in-europe-2015/download. Accessed: 2017-28-01.

Agency, European Environment. 2016. Air quality standards. http://ec.europa.eu/environment/air/quality/standards.htm. Accessed: 2017-28-01.

Agency, United States Environmental Protection. 2015b. Sources of greenhouse gas emissions. https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions. Accessed: 2017-01-19.

Allen, Julian, Garth Thorne, Michael Browne. 2007. Bestufs good practice guide on urban freight transport .

Ando, Naoki, Eiichi Taniguchi. 2006. Travel time reliability in vehicle routing and scheduling with time windows. *Networks and spatial economics* **6**(3) 293–311.

Association, American Trucking. 2011. American trucking industry predicts major industry growth. http://www.genco.com/Logistics-Articles/article.php?aid=800527429. Accessed: 2017-01-010.

BBC. 2015. Italy smog: Milan and rome ban cars as pollution rises. http://www.bbc.com/news/world-europe-35188685. Accessed: 2017-28-01.

Bektaş, Tolga, Gilbert Laporte. 2011. The pollution-routing problem. *Transportation Research Part B: Methodological* **45**(8) 1232–1250.

Bellis, GmbH, BLIC GmbH, IVU Umwelt GmbH, VMZ Betreibergesellschaft mbH. 2010. Abschlussbericht der phase 1. http://uvm-bs.de/sites/default/files/UVM_Stufe_1_Schlussbericht.pdf. Accessed: 2015-09-10.

Bellis, GmbH, BLIC GmbH, IVU Umwelt GmbH, VMZ Betreibergesellschaft mbH. 2012. Abschlussbericht der phase 2. http://uvm-bs.de/sites/default/files/UVM_Stufe_2_Schlussbericht.pdf. Accessed: 2015-09-10.

Bellman, Richard. 1957. A markovian decision process. Tech. rep., DTIC Document.

Bernau, Varinia, Lea Hampel, Nils Wischmeyer. 2016. Her mit den Päckchen, aber bitte schnell und kostenlos. *Süddeutsche Zeitung* URL `http://www.sueddeutsche.de/wirtschaft/liefergesellschaft-alles-immer-bitte-sofort-1.3154867`. [Online; accessed 20-September-2016].

Boltze, Manfred, Sven Kohoutek. 2010. Environment-responsive traffic control. *Proceedings of the World Conference on Transport Research (WCTR), Lissabon, Portugal*.

Bontekoning, Yvonne Margaretha. 2006. *Hub Exchange Operations in Intermodal Hub-and-spoke Operations: Comparison of the Performances of Four Types of Rail-rail Exchange Facilities*. IOS Press.

Brockfeld, Elmar, Robert Barlovic, Andreas Schadschneider, Michael Schreckenberg. 2001. Optimizing traffic lights in a cellular automaton model for city traffic. *Physical Review E* **64**(5) 056132.

Brunekreef, Bert, Stephen T Holgate. 2002. Air pollution and health. *The lancet* **360**(9341) 1233–1242.

Bundesamt, Statistisches. 2011. Transportleistung der verkehrsträger 1950 –2010. `https://www.destatis.de/DE/ZahlenFakten/Wirtschaftsbereiche/TransportVerkehr/Gueterverkehr/Gueterverkehr.html/`.

Bundesamt, Statistisches. 2015a. Fahrleistung von pkw in deutschland bis 2015. `https://de.statista.com/statistik/daten/studie/2984/umfrage/entwicklung-der-fahrleistung-von-pkw/`. Accessed: 2017-01-04.

Bundesamt, Statistisches. 2015b. Transportleistung im deutschen straßengüterverkehr von 2004 bis 2015 (in milliarden tonnenkilometer). `https://de.statista.com/statistik/daten/studie/2979/umfrage/entwicklung-der-transportleistung-des-strassengueterverkehrs/`. Accessed: 2017-01-04.

Cattaruzza, Diego, Nabil Absi, Dominique Feillet, Jesús González-Feliu. 2015. Vehicle routing problems for city logistics. *EURO Journal on Transportation and Logistics* 1–29.

Celikkaya, Nihan, Eftychios Papapanagiotou, Fritz Busch. 2016. Eco-sensitive traffic management. *Digital Mobility Platforms and Ecosystems* 172.

Clarke, Geoff, John W Wright. 1964. Scheduling of vehicles from a central depot to a number of delivery points. *Operations research* **12**(4) 568–581.

CLARS. 2016. Paris emergency scheme. `http://urbanaccessregulations.eu/countries-mainmenu-147/france/paris-odd-even-scheme`. Accessed: 2017-28-01.

Commission, European. 2016a. Fact-finding studies in support of the development of an eu strategy for freight transport logistics lot 1: Analysis of the eu logistics sector.

http://ec.europa.eu/transport/sites/transport/files/themes/strategies/studies/doc/2015-01-freight-logistics-lot1-logistics-sector.pdf. Accessed: 2016-12-07.

Commission, European. 2016b. Freight transport statistics - eurostat. http://ec.europa.eu/eurostat/statistics-explained/index.php/Freight_transport_statistics. Accessed: 2016-12-06.

Crainic, Teodor Gabriel, Michel Gendreau, Jean-Yves Potvin. 2009a. Intelligent freight-transportion systems: Assessment and the contribution of operations research. *Transportation Research Part C: Emerging Technologies* **17**(6) 541–557.

Crainic, Teodor Gabriel, Nicoletta Ricciardi, Giovanni Storchi. 2009b. Models for evaluating and planning city logistics systems. *Transportation science* **43**(4) 432–454.

Dablanc, Laetitia. 2007. Goods transport in large european cities: Difficult to organize, difficult to modernize. *Transportation Research Part A: Policy and Practice* **41**(3) 280–285.

Dantas, Luciano Dionisio, Berichterstatter Prof Friedrich. 2014. *On Modifications to the Traffic-Responsive Urban Control Method*. Shaker.

Dantzig, George B, John H Ramser. 1959. The truck dispatching problem. *Management science* **6**(1) 80–91.

Demir, Emrah, Tolga Bektaş, Gilbert Laporte. 2014. The bi-objective pollution-routing problem. *European Journal of Operational Research* **232**(3) 464–478.

Dijkstra, Edsger W. 1959. A note on two problems in connexion with graphs. *Numerische mathematik* **1**(1) 269–271.

DPD. 2017. Klimaneutraler pakettransport. ohne mehrkosten. https://www.dpd.com/de/home/verantwortung/klimaneutraler_pakettransport. Accessed: 2017-01-19.

Economist, The. 2012. Cities are turning into vast data factoriess. http://www.economist.com/news/special-report/21564998-cities-are-turning-vast-data-factories-open-air-computers/. Accessed: 2017-01-11.

Eglese, Richard, Tolga Bektas. 2014. Green vehicle routing. *Vehicle Routing: Problems, Methods, and Applications* **18** 437.

Eglese, Richard, Will Maden, Alan Slater. 2006. A road timetable to aid vehicle routing and scheduling. *Computers & operations research* **33**(12) 3508–3519.

Ehmke, Jan. 2012. *Integration of information and optimization models for routing in city logistics*, vol. 177. Springer Science & Business Media.

Ehmke, Jan Fabian, Ann Melissa Campbell. 2014. Customer acceptance mechanisms for home deliveries in metropolitan areas. *European Journal of Operational Research* **233**(1) 193–207.

Ehmke, Jan Fabian, Ann Melissa Campbell, Barrett W Thomas. 2016. Vehicle routing to minimize time-dependent emissions in urban areas. *European Journal of Operational Research* **251**(2) 478–494.

Ehmke, Jan Fabian, Dirk Christian Mattfeld. 2010. Data allocation and application for time-dependent vehicle routing in city logistics .

Ehmke, Jan Fabian, André Steinert, Dirk Christian Mattfeld. 2012. Advanced routing for city logistics service providers based on time-dependent travel times. *Journal of Computational Science* **3**(4) 193–205.

eMarketer. 2016. B2c e-commerce sales worldwide from 2012 to 2018 (in billion u.s. dollars). `https://www.statista.com/statistics/261245/b2c-e-commerce-sales-worldwide/`. Accessed: 2016-12-12.

EU. 2008. Directive 2008/50/ec of the european parliament. `http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2008:152:0001:0044:en:PDF`. Accessed: 2016-09-10.

FGSV. 2003. Forschungsgesellschaf für strassen-und t und verkehrswesen: Hinweise zur strategieentwicklung im dynamischen verkehrsmanagement.

FGSV. 2011. Forschungsgesellschaft für strassen-und verkehrswesen (fgsv): Hinweise zur strategieanwendung im dynamischen verkehrsmanagement.

Figliozzi, Miguel. 2010. Vehicle routing problem for emissions minimization. *Transportation Research Record: Journal of the Transportation Research Board* (2197) 1–7.

Figliozzi, Miguel Andres, Lynsey Kingdon, Andrea Wilkitzki. 2007. Analysis of freight tours in a congested urban area using disaggregated data: characteristics and data collection challenges. *Proceedings 2nd Annual National Urban Freight Conference, Long Beach, CA* .

Fleischmann, Bernhard, Stefan Gnutzmann, Elke Sandvoß. 2004. Dynamic vehicle routing based on online traffic information. *Transportation science* **38**(4) 420–433.

für Verkehr und digitale Infrastruktur, Bundesministerium. 2008. Mobilität in deutschland. `http://mobilitaet-in-deutschland.de/mid2008-publikationen.html`. Accessed: 2017-01-05.

Franceschetti, Anna, Dorothée Honhon, Tom Van Woensel, Tolga Bektaş, Gilbert Laporte. 2013. The time-dependent pollution-routing problem. *Transportation Research Part B: Methodological* **56** 265–293.

Friedrich, Bernhard. 1999. *Ein verkehrsadaptives Verfahren zur Steuerung von Lichtsignalanlagen*. Fachgebiet Verkehrstechnik und Verkehrsplanung der Techn. Univ. München.

Fu, Liping. 2002. Scheduling dial-a-ride paratransit under time-varying, stochastic congestion. *Transportation Research Part B: Methodological* **36**(6) 485–506.

Gevaers, Roel, Eddy Van de Voorde, Thierry Vanelslander. 2011. Characteristics and typology of last-mile logistics from an innovation perspective in an urban context. *City Distribution and Urban Freight Transport: Multiple Perspectives, Edward Elgar Publishing* 56–71.

Groß, Patrick-Oliver, Marlin W Ulmer, Dirk C Mattfeld. 2015. Exploiting travel time information for reliable routing in city logistics. *Transportation Research Procedia* **10** 652–661.

Hansen, Pierre, Nenad Mladenović. 1999. An introduction to variable neighborhood search. *Meta-heuristics*. Springer, 433–458.

Hasle, Geir, Oddvar Kloster. 2007. Industrial vehicle routing. *Geometric modelling, numerical simulation, and optimization*. Springer, 397–435.

Hermes. 2017. Hermes we do! nachhaltiger paketversand. `https://www.myhermes.de/wps/portal/paket/Home/privatkunden/we-do`. Accessed: 2017-01-19.

Hertz, Alain, Michel Mittaz. 2001. A variable neighborhood descent algorithm for the undirected capacitated arc routing problem. *Transportation science* **35**(4) 425–434.

Hunt, PB, DI Robertson, RD Bretherton, M Cr Royle. 1982. The scoot on-line traffic signal optimisation technique. *Traffic Engineering & Control* **23**(4).

Hunt, PB, DI Robertson, RD Bretherton, RI Winton. 1981. Scoot-a traffic responsive method of coordinating signals. Tech. rep.

Ichoua, Soumia, Michel Gendreau, Jean-Yves Potvin. 2003. Vehicle dispatching with time-dependent travel times. *European journal of operational research* **144**(2) 379–396.

Inventory, US Emissions. 2005a. Inventory of us greenhouse gas emissions and sinks: 1990–2003. *US Environmental Protection Agency, Washington, DC* .

Inventory, US Emissions. 2005b. National air pollutant emission trends, 1970-2002. *US Environmental Protection Agency, Washington, DC* .

Kampa, Marilena, Elias Castanas. 2008. Human health effects of air pollution. *Environmental pollution* **151**(2) 362–367.

Kellner, Florian. 2016. Exploring the impact of traffic congestion on co2 emissions in freight distribution networks. *Logistics Research* **9**(1) 21.

Kenyon, Astrid S, David P Morton. 2003. Stochastic vehicle routing with random travel times. *Transportation Science* **37**(1) 69–82.

Kim, Gitae, Yew-Soon Ong, Chen Kim Heng, Puay Siew Tan, Nengsheng Allan Zhang. 2015. City vehicle routing problem (city vrp): a review. *IEEE Transactions on Intelligent Transportation Systems* **16**(4) 1654–1666.

Köster, Felix, Marlin W Ulmer, Dirk C Mattfeld. 2015. Cooperative traffic control management for city logistic routing. *Transportation Research Procedia* **10** 673–682.

Köster, Felix, Marlin W Ulmer, Dirk C Mattfeld. 2017a. Dynamic routing: Anticipation of emission-sensitive traffic management. *Transportation Research Procedia* **22** 419–429.

Köster, Felix, Marlin W Ulmer, Dirk C Mattfeld, Geir Hasle. 2017b. Anticipating emission-sensitive traffic management strategies for dynamic delivery routing. *Submitted to Transportation Part D: Transport and Environment* .

Laporte, Gilbert, Francois Louveaux, Hélène Mercure. 1992. The vehicle routing problem with stochastic travel times. *Transportation science* **26**(3) 161–170.

Larsen, Allan, OBGD Madsen, Marius Solomon. 2002. Partially dynamic vehicle routing-models and algorithms. *Journal of the Operational Research Society* 637–646.

Lecluyse, Christophe, Tom Van Woensel, Herbert Peremans. 2009. Vehicle routing with stochastic time-dependent travel times. *4OR* **7**(4) 363–377.

Li, Xiangyong, Peng Tian, Stephen CH Leung. 2010. Vehicle routing problems with time windows and stochastic travel and service times: Models and algorithm. *International Journal of Production Economics* **125**(1) 137–145.

Lorini, Sandro, Jean-Yves Potvin, Nicolas Zufferey. 2011. Online vehicle routing and scheduling with dynamic travel times. *Computers & Operations Research* **38**(7) 1086–1090.

Lourenço, Helena R, Olivier C Martin, Thomas Stützle. 2003. Iterated local search. *Handbook of metaheuristics*. Springer, 320–353.

Ltd, DHL International (UK). 2012. Dhl gogreen services. `http://www.dhl.co.uk/content/dam/downloads/gb/express/services/gogreen/gogreen_service_sheet_gb_en.pdf`. Accessed: 2016-12-05.

Malandraki, Chryssi, Robert B Dial. 1996. A restricted dynamic programming heuristic algorithm for the time dependent traveling salesman problem. *European Journal of Operational Research* **90**(1) 45–55.

McCarthy, Linda Mary, Paul Leslie Knox. 2005. *Urbanization: An introduction to urban geography*. Pearson Prentice Hall.

McKinnon, Alan, Julia Edwards, Maja Piecyk, Andrew Palmer. 2009. Traffic congestion, reliability and logistical performance: a multi-sectoral assessment. *International Journal of Logistics: Research and Applications* **12**(5) 331–345.

Meisel, Stephan. 2011. *Anticipatory optimization for dynamic decision making*, vol. 51. Springer Science & Business Media.

Miller-Hooks, Elise D, Hani S Mahmassani. 2000. Least expected time paths in stochastic, time-varying transportation networks. *Transportation Science* **34**(2) 198–215.

Ministerium für Umwelt, Gesundheit und Verbraucherschutz. 2016. Luftreinhalte- und qualitätsplan für die landeshauptstadt potsdam. `http://www.lfu.brandenburg.de/cms/media.php/lbm1.a.3310.de/lrp_pdm_sb.pdf`. Accessed: 2017-28-01.

Nemoto, Toshinori, Johan Visser, Ryuichi Yoshimoto. 2001. Impacts of information and communication technology on urban logistics system. *Joint OECD/ECMT Seminar on the impacts of E-commerce on Transport*. Citeseer, 1–19.

NEWS, BBC. 2016. Polluted delhi has 'become a gas chamber'. `http://www.bbc.com/news/world-asia-india-37856875`. Accessed: 2017-01-19.

NEWS, BBC. 2017. Beijing: The city where you can't escape smog. `http://www.bbc.com/news/magazine-385875801`. Accessed: 2017-01-19.

Nuhn, Helmut, Markus Hesse. 2006. *Verkehrsgeographie*. Schöningh (UTB).

of Logistics Management (U.S.), Council. 1999. *What It's All About–purpose, Objectives, Programs, Policies*. The Council. URL `https://books.google.de/books?id=9geFnQEACAAJ`.

OpenStreetMap Contribution. 2017. Planet dump retrieved from https://planet.osm.org . `https://www.openstreetmap.org`.

Pillac, Victor, Michel Gendreau, Christelle Guéret, Andrés L Medaglia. 2013. A review of dynamic vehicle routing problems. *European Journal of Operational Research* **225**(1) 1–11.

Pisinger, David, Stefan Ropke. 2007. A general heuristic for vehicle routing problems. *Computers & operations research* **34**(8) 2403–2435.

Pohlmann, Tobias. 2011. *New approaches for online control of urban traffic signal systems*. Shaker.

Potsdam, Stadt. 2016. Erste ergebnisse der evaluierung der umweltorientierten verkehrsteuerung. `https://www.potsdam.de/content/042-potsdamer-luftqualitaet-verbessert`. Accessed: 2017-28-01.

PTV. 2012. Ptv verstärkt aktivitäten in der verkehrsmanagement-welt. `http://newsroom.ptvgroup.com/en-uk/press/singleview/news/ptv-verstarkt-aktivitaten-in-der-verkehrsmanagement-welt-39/7499/`. Accessed: 2017-01-27.

Puterman, Martin L. 2014. *Markov decision processes: discrete stochastic dynamic programming*. John Wiley & Sons.

Rosen, Robert. 2012. *Anticipatory systems*. Springer.

Rosenkrantz, Daniel J, Richard E Stearns, Philip M Lewis, II. 1977. An analysis of several heuristics for the traveling salesman problem. *SIAM journal on computing* **6**(3) 563–581.

Rosenkrantz, Daniel J, Richard Edwin Stearns, PM Lewis. 1974. Approximate algorithms for the traveling salesperson problem. *Switching and Automata Theory, 1974., IEEE Conference Record of 15th Annual Symposium on*. IEEE, 33–42.

Schilde, Michael, Karl F Doerner, Richard F Hartl. 2014. Integrating stochastic time-dependent travel speed in solution methods for the dynamic dial-a-ride problem. *European journal of operational research* **238**(1) 18–30.

Schnabel, Werner, Dieter Lohse. 2011a. *Grundlagen der Straßenverkehrstechnik und der Verkehrsplanung: Band 1-Straßenverkehrstechnik*, vol. 1. Beuth Verlag.

Schnabel, Werner, Dieter Lohse. 2011b. *Grundlagen der Straßenverkehrstechnik und der Verkehrsplanung: Band 2-Verkehrsplanung*. Beuth Verlag.

Service, United Parcel. 2016. Shipping carbon neutral with ups. `https://www.ups.com/content/us/en/resources/ship/carbonneutral/shipping.html?srch_pos=2&srch_phr=carbon+neutral`. Accessed: 2016-12-05.

Statista. 2015. Statista - average speed in europe's 15 most congested cities in 2008 (in kilometers per hour). `https://www.statista.com/statistics/264703/average-speed-in-europes-15-most-congested-cities/`. Accessed: 2015-09-10.

Susilawati, Susilawati, Michael AP Taylor, Sekhar VC Somenahalli. 2013. Distributions of travel time variability on urban roads. *Journal of Advanced Transportation* **47**(8) 720–736.

Taniguchi, E, Russell G Thompson, T Yamada. 1999. Modelling city logistics. *International conference on city logistics, 1ST, 1999, Cairns, Queensland, Australia*.

Taniguchi, Eiichi, Hiroshi Shimamoto. 2004. Intelligent transportation system based dynamic vehicle routing and scheduling with variable travel times. *Transportation Research Part C: Emerging Technologies* **12**(3) 235–250.

Taniguchi, Eiichi, Russell G Thompson. 2002. Modeling city logistics. *Transportation Research Record: Journal of the Transportation Research Board* **1790**(1) 45–51.

Taniguchi, Eiichi, Russell G Thompson. 2011. *City Logistics Network Modelling and Intelligent Transport Systems*.

Taniguchi, Eiichi, Russell G Thompson. 2014. *City logistics: Mapping the future*. CRC Press.

Taniguchi, Eiichi, Russell G Thompson, Tadashi Yamada, Ron Van Duin. 2001. *City Logistics. Network modelling and intelligent transport systems*.

Ulmer, Marlin W, Justin C Goodson, Dirk C Mattfeld, Barrett W Thomas. 2016. Route-based Markov decision processes for dynamic vehicle routing problems. *Submitted* .

Ulmer, Marlin Wolf. 2017. *Approximate Dynamic Programming for Dynamic Vehicle Routing*. Springer.

Van Woensel, Tom, Laoucine Kerbache, Herbert Peremans, Nico Vandaele. 2008. Vehicle routing with dynamic travel times: A queueing approach. *European journal of operational research* **186**(3) 990–1007.

Xiang, Zhihai, Chengbin Chu, Haoxun Chen. 2008. The study of a dynamic dial-a-ride problem under time-dependent and stochastic environments. *European Journal of Operational Research* **185**(2) 534–551.

Yan, Shangyao, Jenn-Rong Lin, Chun-Wei Lai. 2013. The planning and real-time adjustment of courier routing and scheduling under stochastic travel times and demands. *Transportation Research Part E: Logistics and Transportation Review* **53** 34–48.

Yang, Qi, Haris N Koutsopoulos. 1996. A microscopic traffic simulator for evaluation of dynamic traffic management systems. *Transportation Research Part C: Emerging Technologies* **4**(3) 113–129.